Energy Intelligence

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Review

Energy Intelligence: A Systematic Review of Artificial Intelligence for Energy Management

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Abstract: Artificial intelligence (AI) and machine learning (ML) can assist in the effective development of the power system by improving reliability and resilience. The rapid advancement of AI and ML is fundamentally transforming energy management systems (EMSs) across diverse industries, including areas such as prediction, fault detection, electricity markets, buildings, and electric vehicles (EVs). Consequently, to form a complete resource for cognitive energy management techniques, this review paper integrates findings from more than 200 scientific papers (45 reviews and more than 155 research studies) addressing the utilization of AI and ML in EMSs and its influence on the energy sector. The paper additionally investigates the essential features of smart grids, big data, and their integration with EMS, emphasizing their capacity to improve efficiency and reliability. Despite these advances, there are still additional challenges that remain, such as concerns regarding the privacy of data, challenges with integrating different systems, and issues related to scalability. The paper finishes by analyzing the problems and providing future perspectives on the ongoing development and use of AI in EMS.

Keywords: artificial intelligence; machine learning; energy management systems; smart grids; power systems; renewable energy sources (RESs)

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1. Introduction

1.1. Overall Insights

Energy systems are transitioning to integrate renewable technologies and improve efficiency; however, increasing complexities associated with their uncertainties make controlling energy flows challenging [1]. Consequently, a wide range of artificial intelligence (AI) models can be integrated to have improved energy management systems (EMSs) considering the increasing usage of renewable energy resources (RESs). In this regard, scrutinizing a comprehensive overview of these applications will be beneficial (a review of previous 44 overview papers has been conducted in this section too). A large number of researchers are presenting research works or overviews to facilitate the use of AI in smart EMS in the power system sector. In this respect, the total number of publications (year range of 2005–nearly 2025) in this subject with the related sectors is manifested in Figure 1, based on the Scopus scientific portal. The publications intended in the proposed statistics are the manuscript types of journal papers, conference papers, book chapters, books, and editorial notes. The authors of [2] reviewed 24 machine learning (ML) algorithms, revealing Bagged Trees, Fine Trees, and Medium Trees as the best-performing algorithms. However, efficiency was reversed, which became the top efficiency for Bagged Trees and Medium Trees. Fine Trees had the best tradeoff between efficacy and efficiency. The research conducted in [3] used VOSviewer in order to analyze AI and ML usage in the power sector, revealing research trends and promising areas that needed to be developed. The study also shows a sharp increase in patents submitted and presented for the applications of

AI and ML in energy-related areas. As well, ML models in energy systems are reviewed in [4] that highlighted their advancements and applications. A taxonomy of models and their applications is presented, evaluating their accuracy, robustness, precision, and generalization ability. The study concludes that hybrid ML models are effective in RESs EMS and operation management, particularly solar, wind, and biofuels. On the other hand, hybrid models contribute to energy efficiency, governance, and sustainability, making them important for energy systems.

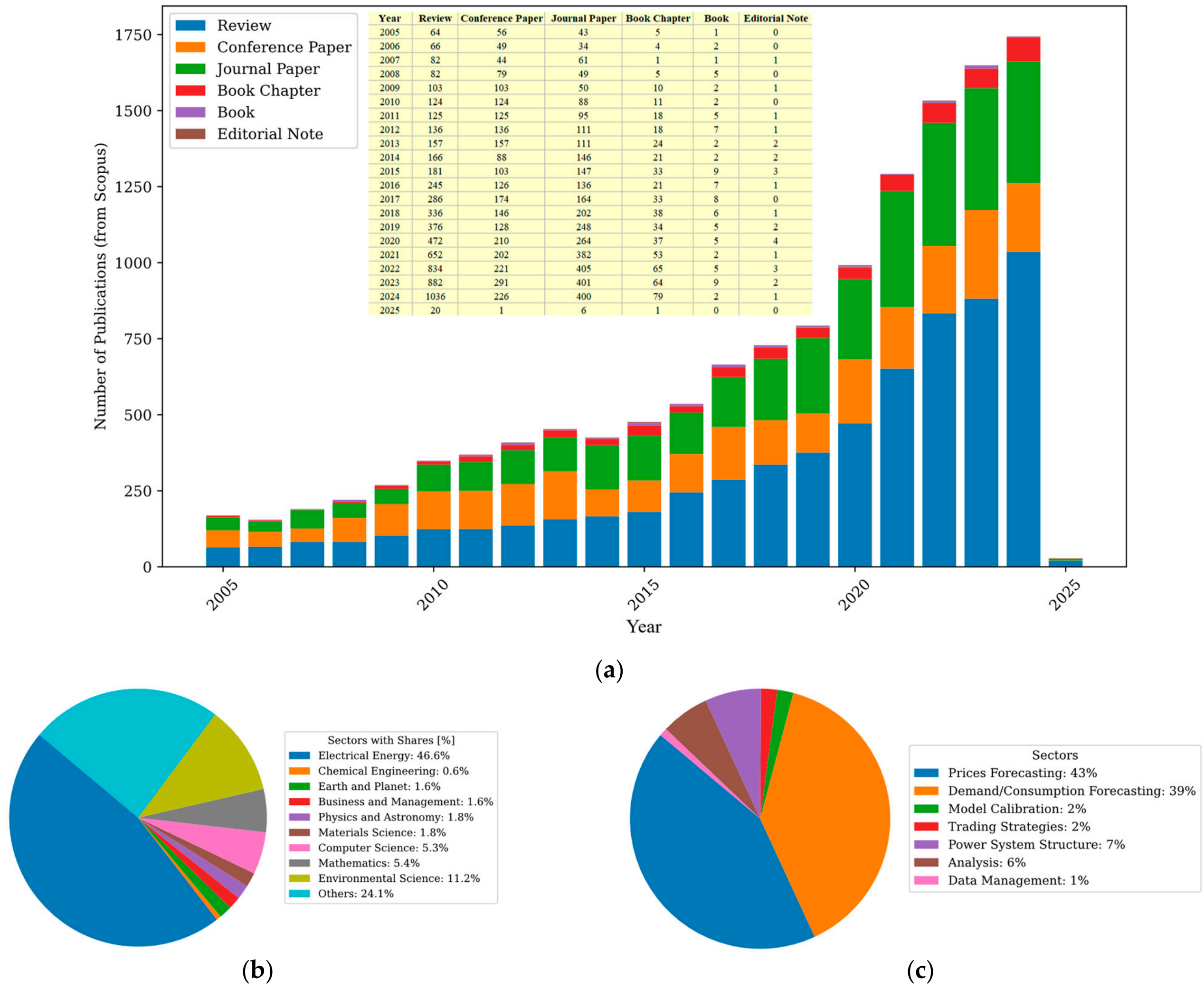

Figure 1. Analytics over (**a**) 2005–nearly 2025 Scopus-indexed number of publications of EMS, (**b**) AI overall applications, and (**c**) use of AI in EMS.

From the financial perspective, ML is applied to energy economics and finance with applications, including price forecasting, demand prediction, risk management, trading, data mining, and infrastructure deployment, on the trend study. Consequently, the study [5] investigates artificial neural networks (ANNs) and support vector machines (SVM) in the mentioned areas. A similar study [6] shows the coordination importance in the generation, storage, and management of renewables within a microgrid cluster. It highlights the importance of better grid infrastructure, energy storage innovations, as well as approaches using cloud computing and ML. It lays out important components for a cloud-based architecture, such as real-time simulations, virtual server links, and cloud-hosted EMS. It introduces a scalable and self-sufficient architecture, taking advantage of ML methodologies to forecast power generation and real-time energy management. CO_2 reduction is achieved by the growing market penetration of hybrid energy systems (HESs), which include RES like wind and solar energy [7]. The EMS is regarded as important in HES for avoiding blackouts, and the latest research discusses enhancing the EMS of these systems by using ML algorithms, including Random Forest (RF), Decision Tree (DT), Gaussian Naive Bayes (GNB), and K-Nearest Neighbors (KNNs). The results indicate that the DT algorithm is generally more effective; RF, GNB, and others are reported to perform well too; however, DT has been found to be the most accurate in terms of predictive performance.

1.2. Methodology and Literature Selection

As well, the overall logic of the literature review selection of this paper is manifested in Figure 2.

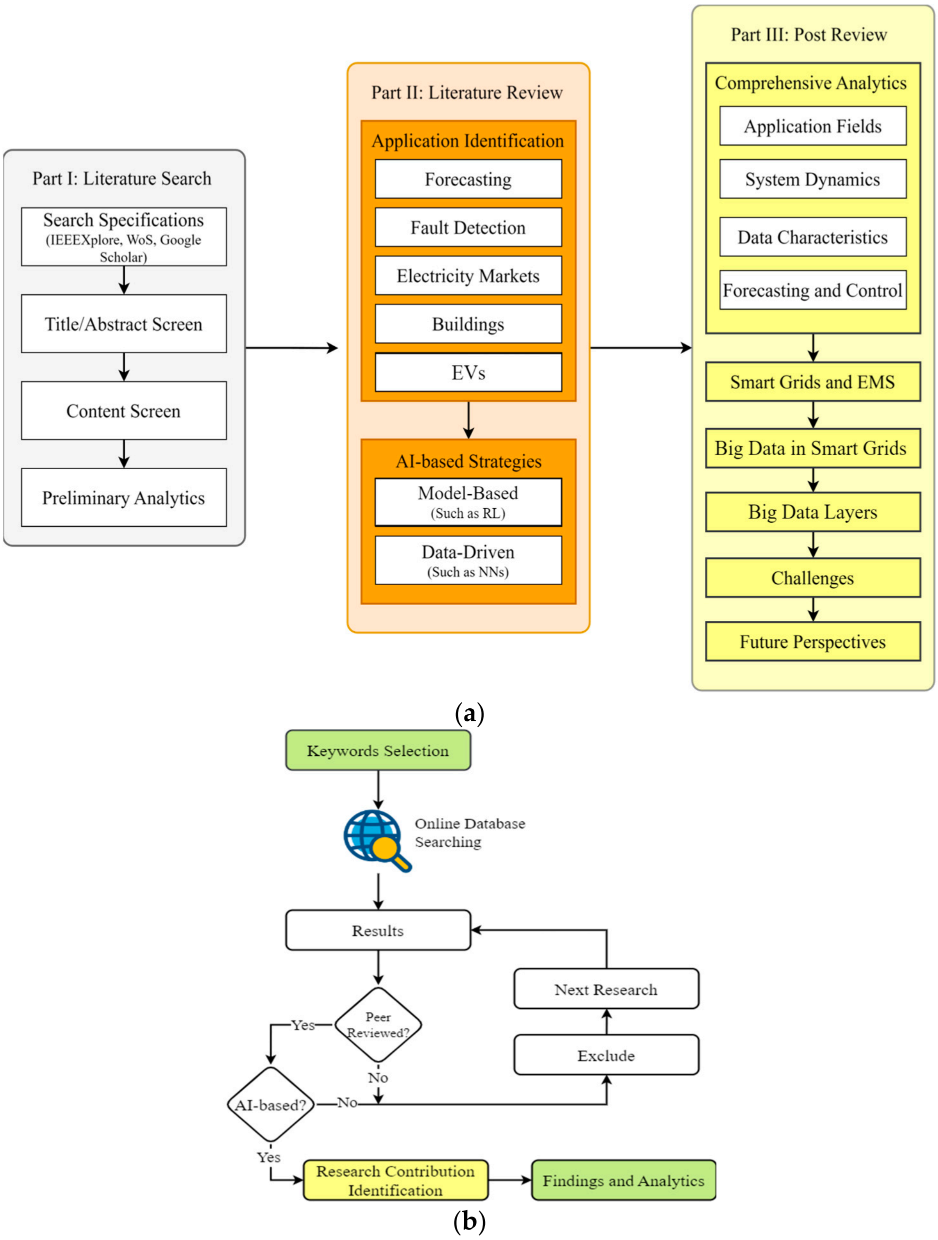

Figure 2. Overall (**a**) three phases of research structure and (**b**) framework of literature review selection.

Keywords are picked to perform research on the topic of EMS in the energy sector. These are the keywords that were entered in the *Online Database Searching* step to search for the literature over different databases (*IEEEXplore, Google Scholar, Web of Science, ScienceDirect, Wiley Online Library, MDPI, and Springer Nature*). They get the search results and they are evaluated. The first consideration is that the results are peer-reviewed. If a source is not peer-reviewed, it is excluded, and if so, proceeds to the next indicator. If the source is peer-reviewed and integrates the application of AI in EMS, it goes to the next step of contribution identification, which determines the highlighted contributions of the research. If it is non-AI-based, then it goes to be excluded. In the last phase, it brings together the contributions identified previously and makes an analysis that summarizes what was investigated in this overview paper.

1.3. Literature in Power Grids

Recent ML strategies for reliability and power energy systems control, specifically large-scale electric power systems, are reviewed in [8]. The study aims to unite current advances in the ML-related reliability literature while incorporating system-level management aspects through this study and offering use-cases for distribution grid, microgrid, and multi-energy systems. It makes the case that microgrids will be foundational for fulfilling worldwide energy needs and that grid decentralization is critical. Therefore, the need for intelligent and reliable EMS is mandatory to sustain their operation. AI in this regard provides solutions that are robust and scalable, powered by advanced algorithms. Accordingly, the comparison between the conventional and AI-based methods for EMS in microgrids is conducted in [9] looking at centralized, decentralized, and distributed systems. However, some privacy challenges of data, security, scalability, and explainability need to be solved. In [10], the recent ML approaches for EMS across residential and industrial sectors are discussed with the diversity of algorithms used, such as reinforcement learning (RL), DRL-based, and path integral-based control strategies. It evaluates the role in future communication technologies, addressing cyber-physical systems and IoT-based communication sensors, considering ML issues related to emergency measures for integrity protection, as well as its incorporation into existing control mechanisms. Moreover, Ref. [11] manifests hybrid methodologies by integrating optimization and ML techniques for clustering and classification with the perspective, which is trying to identify what challenges each methodology has so insights can be provided regarding the potential of their combination.

The study in [12] examines the RES energy global adoption, such as solar and wind, emphasizing both their advantages and limitations. It discusses the growth of these RES, current trends, and emerging technologies. Given the high increase in the universal demand for energy, the development of new materials for RES technologies becomes considerably important. Traditional methods for material discovery are often expensive and time-consuming, which has led to the rise of ML as a research tool. In this context, Ref. [13] reviews ML approaches, algorithms, and advancements in material property prediction and developing energy-related materials. Lithium-ion batteries in ESSs, EVs, and portable electronics have challenges, such as overheating and aging, as they have high energy density. Battery management systems (BMSs) are essential for ensuring safe operation; however, accurate predictions performed on the state of health (SoH), state of charge (SoC), and remaining useful life are important too. To address this concern, Ref. [14] reviews ANN-based methods for predicting battery conditions, highlighting current trends and gaps in BMS applications. Additionally, physics-informed ML (PIML) techniques are gaining attention for improving model generalization, adherence to physical laws, and interpretability. Based on this, Ref. [15] provides an overview of PIML applications in subsurface EMS, with a study on seismic activities, reservoir simulations, hydrocarbon production forecasting, and intelligent decision-making.

Considering other applications of AI/ML in EMS, forecasting is among the other important applications. The supplied/demanded power balance is important in the power energy dispatches. This balance is maintained through demand response programs, one in particular called short-term load forecasting (STLF). STLF with the integration of volatility and uncertainties in load demand by deep learning-based prediction has been considered for STSF [16], which emphasized accuracy and performance metrics that advance DL techniques, proposing future research directions related to online incorporation or operation, volatility robustness, and feasibility. In [17], a unified EMS is presented for energy management and interhousehold sharing with the help of ML and blockchain. Using ML to forecast energy generation and building a bidding system on top of it in order to distribute this automated power through peer-to-peer (P2P) transactions. It not only balances supply/demand, but it also supports prosumer-consumer direct energy trading, which incurs more computational complexity while still having better performance in terms of balancing charges, workload division, and capital costs.

The study in [18] reviews district heating and cooling networks, smart EMS, and control strategies through multidisciplinary approaches, considering both heating and cooling aspects. It proposes an energy migration framework for intercity transportation to facilitate energy sharing and regional balance. The study also emphasizes the technical feasibility of ML methods for energy planning and optimization. A district energy network is modeled using RES, waste heat recovery, and diversified energy storage systems (ESSs). Future research should focus on addressing technical challenges, establishing benchmarks, managing energy congestion, and incorporating multicriteria decision-making. The depletion of fossil fuels has triggered an energy crisis, making RES essential. As discussed in [19], EMS strategies are mostly taken into account for improving power system reliability and mitigating climate change risks, with EMS as the important component. The study also manifests the importance of AI in enhancing smart grid technologies and managing load uncertainties. Another study in [20] reviews 135 publications on offshore wind energy, turbine control, wind farm wake management, and layout optimization. It examines AI technology applications, such as fuzzy logic, DL, and RL. Additionally, Ref. [21] reviews ML-based predictive maintenance in microgrid systems, highlighting how to enhance efficiency, safety, and sustainability. The study reviews recent techniques, identifies gaps, and recommends future research directions.

The role of AI in power distribution systems is reviewed in [22] about electrical power load forecasting, fault detection, and demand response strategies. This study is presented on selecting appropriate AI models while evaluating the pros and cons of various learning methods. It also addresses the incentive and price-based demand response program implementation, taking into account control objectives, input sources, and applications. DC microgrids are now considered significant due to their adoption, solar PV systems, and energy storage technology integration, alongside their challenges related to frequency and reactive power control. Key factors for a stable and reliable DC microgrid include controlling DC bus voltage, power management, and SoC restoration. Control strategies for DC microgrids are considered using centralized/decentralized approaches in addition to distributed, multi-level, as well as hierarchical systems, along with advanced methodologies of nonlinear control, robust control, model predictive control (MPC), and AI-based methods. The study in [23] analyzes these elements by identifying research gaps and the directions for the need for additional development. Research presented in [24] investigates PV system utilization, desalination technologies, AI, and ML in water desalination processes. It assesses recent advancements, identifies trends, and explores the influence of AI and ML on PV system performance, maintenance, and monitoring. The significance of developing virtual power plants (VPPs) is considered in [25], approached from a data-centric perspective that analyzes energy management across the data lifecycle. This study reviews advancements in data mining, advanced communication technologies, decision support methods, security and privacy, RL, P2P sharing, blockchain, and market participation. Additionally, it addresses the challenges and opportunities in areas such as IoT, 5G technology, publicly available benchmarks, explainable AI, and federated learning, providing the necessity for technological data management advancements and support systems for future VPP initiatives.

The AI-smart grids integration enhances flexibility, facilitates maintenance, and allows for adaptable energy distribution. Additionally, advancements in hydrogen energy, driven by data privacy legislation, grid modernization, and incentives, are discussed in [26]. The study in [27] presents future research related to smart grids and urban EMS, categorizing these into physical, cyber, and social energy systems. The global climate crisis and the depletion of traditional energy sources have led to increased demand for RES. However, intermittent sources such as wind and solar cannot be fully regulated or pre-planned. To this end, ML is an emerging technology used to predict and detect faults in RES, thus reducing operational and maintenance costs. Techniques reviewed in ML are employed for fault prediction, early detection, and diagnosis, ensuring continuous power supply to loads, as indicated in [28]. Furthermore, over 10 regular algorithms for modeling and optimizing RES are discussed in [29], including ANN, LSTM, RNN, genetic algorithms (GAs), and particle swarm optimization (PSO). The findings are compiled from more than 100 studies conducted between 2020 and 2022. The review in [30] manifested distributed energy sources and their integration into utility grids, presenting microgrids as self-sustaining systems with distributed resources. It evaluates decision-making strategies, methods for quantifying uncertainty, communication technologies, and future directions for distributed energy resource integration in microgrids, while also providing insights into real-world applications.

Advantages of Section 1.3 (Literature in Power Grids): The proposed literature in the power grids covered overviews of AI and ML applications in energy systems, including many benefits and drawbacks. One such benefit is that AI and ML models can optimize energy management via predictive maintenance, load forecasting, and anomaly detection, leading to improvements in efficiency, reliability, and operational flexibility. The implementation of these models can lead to data-driven decision-making in real-time and adaptive control for more advanced energy systems, including superior resources and lower operational costs. Scalability and application to a specific sector (e.g., microgrid integration, VPPs, and RES) are possible through hybrid modeling approaches that incorporate optimization with ML. Emerging technologies such as blockchain for decentralized energy management and AI for smart grid integration represent a potential step up too.

Disadvantages of Section 1.3 (Literature in Power Grids): However, the studies also have limitations. Many AI and ML models face challenges with computational costs, high data demands, and difficulties in handling complex, real-time energy networks. Scalability remains an issue, especially when moving from small-scale implementations to larger grid applications. While some models excel in specific domains, such as load management or renewable energy forecasting, they often struggle with generalizability across different energy sectors. Furthermore, technologies, like blockchain, come with significant energy costs that can offset sustainability benefits. Lastly, despite the potential of predictive models, practical adoption is limited by having a few case studies and the lack of standardized frameworks, which restrict widespread implementation in real-world energy systems.

1.4. Literature in Smart Buildings

On the side of AI applications in buildings, several aspects, such as financially and technically, are considered important. Smart building systems are enabled by AI technologies, which can optimize energy consumption by adjusting lighting, heating, and cooling in real time based on occupancy and utilization patterns. This reduces energy costs and environmental impact. AI-driven predictive maintenance can forecast equipment failures and facilitate timely repairs, minimizing downtime and prolonging the lifespan of building infrastructure. Additionally, AI-enhanced security systems have advanced surveillance and threat detection features, ensuring a safer environment for occupants. The AI integration makes buildings more responsive, adaptable, and efficient, aligning with the demands of modern urban living and aiding in the development of more resilient and intelligent cities. Research in [31] reviews ML methods for predicting energy demand in modern buildings, focusing on their accuracy and efficiency in minimizing energy consumption. Furthermore, a systematic review in [32] evaluates smarter cities and artificial IoT (AIoT) solutions aimed at promoting green energy and sustainability. This review investigates the foundational principles of these cities, their relationships with urbanism paradigms, green energy transition, data-driven technologies/methodologies, key factors, essential

AI and AIoT solutions, their role in advancing green environmental practices, and their implementation challenges. The gained perspectives enhance the potential of AI and AIoT technologies to improve sustainable urban development practices and further integrate eco-urbanism with AI- and AIoT-driven urbanism. In addition to simulation tools, building energy management (BEM) is important too, and these tools are for evaluating building performance. Accordingly, the review conducted in [33] manifested various modeling approaches, including white box, black box, and web tool models, in addition to the simulation scales. The goal is to identify the advantages and weaknesses of the proposed strategies. The study [34] reviews techniques based on ML and DL for managing building energy systems and evaluating their effectiveness. The findings indicate that hybrid and ensemble methods have higher robustness, while DL-based, hybrid, and ensemble-based models achieve the highest robustness scores. In contrast, ANN, SVM, and individual ML models demonstrate varying levels of robustness.

Also, an overview of interpretable ML techniques is reviewed in [35] for BEM on both ante-hoc and post-hoc approaches. The challenges include varying terminologies, difficulties in comparing the performance of interpretable ML methods, and the limited interpretability of current techniques. Future research should be more focused on enhancing the interpretability of black-box models. Improving energy efficiency in the building sector is important for reducing CO_2 gas emissions and fossil fuel consumption. Early design considerations, energy management, and smart renovations can facilitate this goal. Various AI and machine learning techniques, including NNs, SVMS, gradient boosting regressors (GBRs), and clustering methods, can be utilized to forecast and enhance building energy performance, as reviewed in [36]. On the other side, optimal planning and the associated methods are necessary to enhance home EMS (HEMs) to meet demand requirements [37–39]. Accurate load forecasting and scheduling are also important components of HEMs. ML techniques have been taken into account for smart HEM and for autonomously controlling heating and domestic hot water systems. The growing number of homes equipped with RES is increasing too for optimizing energy usage. AI technologies can be taken into account to reduce energy usage through improved control systems. Future research should investigate the role of AI during the construction phase for considering energy-efficient facility construction systems techniques and control strategies.

Advantages of Section 1.4 (Literature in Buildings): The literature in buildings on EMS emphasizes the role of AI and ML in optimizing energy usage and enhancing control strategies within building systems. Key advantages include the predictive capabilities of ML models for demand forecasting, which allow for adaptive EMS based on real-time data, thereby reducing waste and lowering costs. These technologies support the automation of energy controls in modern buildings and smart homes, improving user comfort and operational efficiency. Furthermore, DL and RL applications enable advanced control strategies that can respond to dynamic energy pricing and environmental conditions.

Disadvantages of Section 1.4 (Literature in Buildings): Despite these advantages, there are also some critical limitations that need to be addressed in the building's energy management area. High computational requirements and data demands cause these models difficult to implement in older buildings or in settings with limited infrastructure. Furthermore, while RL and other black-box approaches excel in adaptability, their lack of interpretability can hinder their acceptance in consulting and decision-making contexts. Interoperability challenges are also prevalent, as AI applications often require integration with diverse building management systems and IoT devices. Lastly, DL models can have the problem of overfitting in energy systems with limited historical data, which impacts their reliability in varied operational scenarios.

1.5. Literature in EVs

Finally, considering the AI integration in EVs, AI-powered systems enhance BMS, expand battery life, and improve safety through autonomous driving and real-time navigation. Additionally, AI supports predictive maintenance, lowers maintenance costs, and personalizes the driving experience, resulting in more reliable and user-friendly EVs. The Internet of Vehicles (IoVs) connects vehicles equipped with sensors to a broader network, proposed to improve driving comfort, EMS, secure data transmission, and accident prevention. However, it faces challenges related to security and trust management. A survey in [40] manifests an overview of the IoV and the role of ML in enhancing its security framework, providing strategies into trust and security improvements. The growing environmental challenges, such as air pollution, increasing CO_2 gas emissions, and global warming, make the requests for clean energy resources. Hybrid electric vehicles (HEVs) represent a solution to reduce fossil fuel consumption and address environmental concerns. In this regard, EMSs are a critical aspect of HEV design, focusing on power distribution across multiple energy sources. AI, ML, and data-driven intelligent controllers have made advancements in EMS strategies that can be applicable for HEVs [41]. In this context, the studies [42,43] review ML and intelligent concepts for prediction, control methods, EMS, and vehicle-to-everything (V2X) interactions in hydrogen fuel cell vehicles (HFCV). Additionally, the data-driven control and optimization systems are reviewed, along with discussions on future trends and sustainability directions. Recent developments in deep reinforcement learning (DRL) show opportunity for addressing relevant challenges. As a result, the literature in [44,45] surveys DRL-based EMSs, comparing RL strategies with dynamic programming control approaches. Simulations demonstrate that RL strategies can achieve optimal control problems with an infinite horizon, similar to what is attained through stochastic dynamic programming.

Advantages for Section 1.5 (Literature in EVs): The literature on energy management in EVs presented the integration of AI and ML to optimize energy usage and enhance EVs' performance. The advantages of these approaches include improvements in energy efficiency, extended driving range, and reduced CO_2 emissions. ML algorithms, including DRL, cause advanced decision-making for real-time power distribution, driving conditions adaptation, and enhancing battery remaining useful life (RUL). Furthermore, these strategies facilitate the optimization of fuel consumption in hydrogen vehicles and the coordination of energy flows between power sources in hybrid systems.

Disadvantages for Section 1.5 (Literature in EVs): However, several challenges remain. The complexity of implementing DL and RL algorithms can lead to high computational costs, which may limit their application in real-time systems. Additionally, the need for large training datasets can impact model accuracy, particularly in newer or less-tested energy systems. Hybrid systems and hydrogen fuel cell technologies also face integration issues, as their efficiency relies on complex coordination between several power sources, which can be challenging to manage effectively. Furthermore, the application of AI in EMS for vehicles requires infrastructure for data collection and real-time implementation.

Therefore, the surveyed review papers are summarized in Table 1.

Table 1. Summary of surveyed papers.

References	Power Grids	Buildings	Electricity Markets	EVs
[1]	✓	✗	✗	✗
[2]	✓	✗	✗	✗
[3]	✓	✗	✗	✗
[4]	✓	✗	✗	✗
[5]	✓	✗	✓	✗
[6]	✓	✗	✗	✗
[7]	✓	✗	✗	✗
[8]	✓	✗	✗	✗
[9]	✓	✗	✗	✗
[10]	✓	✓	✗	✗
[11]	✓	✗	✗	✗
[12]	✓	✗	✗	✗
[13]	✓	✗	✗	✓
[14]	✓	✗	✗	✓

Table 1. *Cont.*

References	Power Grids	Buildings	Electricity Markets	EVs
[15]	✓	✗	✗	✗
[16]	✓	✗	✓	✗
[17]	✓	✗	✓	✗
[18]	✓	✗	✗	✗
[19]	✓	✗	✗	✗
[20]	✓	✗	✗	✗
[21]	✓	✗	✗	✗
[22]	✓	✗	✓	✗
[23]	✓	✗	✗	✗
[24]	✓	✗	✓	✗
[25]	✓	✗	✗	✗
[26]	✓	✗	✓	✗
[27]	✓	✗	✗	✗
[28]	✓	✗	✗	✗
[29]	✓	✗	✗	✗
[30]	✓	✗	✗	✗
[31]	✗	✓	✓	✗
[32]	✗	✓	✗	✗
[33]	✗	✓	✗	✗
[34]	✗	✓	✗	✗
[35]	✗	✓	✗	✗
[36]	✗	✓	✗	✗
[37–39]	✗	✓	✓	✗
[40]	✗	✗	✗	✓
[41]	✗	✗	✗	✓
[42,43]	✗	✗	✗	✓
[44,45]	✓	✗	✗	✗
Proposed	✓	✓	✓	✓

1.6. Objectives and Contributions

Referring to Table 1, the previously published review papers were conducted on power systems, with some of them dealing with two subjects of power grids-electricity markets, power grids-EVs, or buildings-electricity markets. This manifests that they could not cover recent literature of all fields of power grids, buildings, EVs, and electricity markets to have a complete overview of AI in the EMS of the energy sector. Consequently, based on the surveyed literature of review papers about EMS in energy systems, this paper is motivated and aimed to review a wide range of overview studies, more than 200 recent papers (45 reviews and more than 155 research studies) in EMS of smart grids, microgrids, EVs, buildings, and their integration while presenting their concepts in the related sections. Based on this gap, the authors of the proposed review paper identified that it is practical and worthy of investigation.

In this regard, the main contributions of the paper are summarized as follows:

- Reviewed 200+ papers (45 reviews and more than 155 research studies) on AI/ML in EMS, forecasting, fault diagnosis, electricity markets, buildings, and electric vehicles (EVs), considering different types of EVs, such as battery-based, hybrid, plug-in, and fuel cells.
- Manifested advantages and disadvantages for each literature (Sections 1.3–1.6).
- Presented big data's important role in improving EMS efficiency and scalability.
- Identified challenges in AI/ML adoption and suggested future research directions.
- Provided a framework for comprehension of AI, ML, and big data in smart grids and EMS.

1.7. Paper Structure

The paper is structured as follows:

Sections 1 and 2 provide details about smart grids, EMS, and the importance of big data within these systems, respectively. AI and ML models are described in Section 3. Section 4 reviews the strategies used in forecasting, fault detection, the electricity market, buildings, and EVs, respectively. Moreover, the challenges and future perspectives of AI-driven EMS are presented in Section 5, and Section 6 discusses future perspectives. Finally, Section 7 draws the conclusion of the paper.

2. Smart Grids and Energy Management Systems

A smart grid, with intelligent EMS, functions as an intelligent network that integrates information technology with the existing energy system infrastructure [46]. This integration allows utilities to gather diverse energy data from the network using intelligent sensors (such as smart meters, emission monitors, etc.) and rapid communication systems, facilitating effective demand and supply balancing [47] as conceptualized in Figure 3.

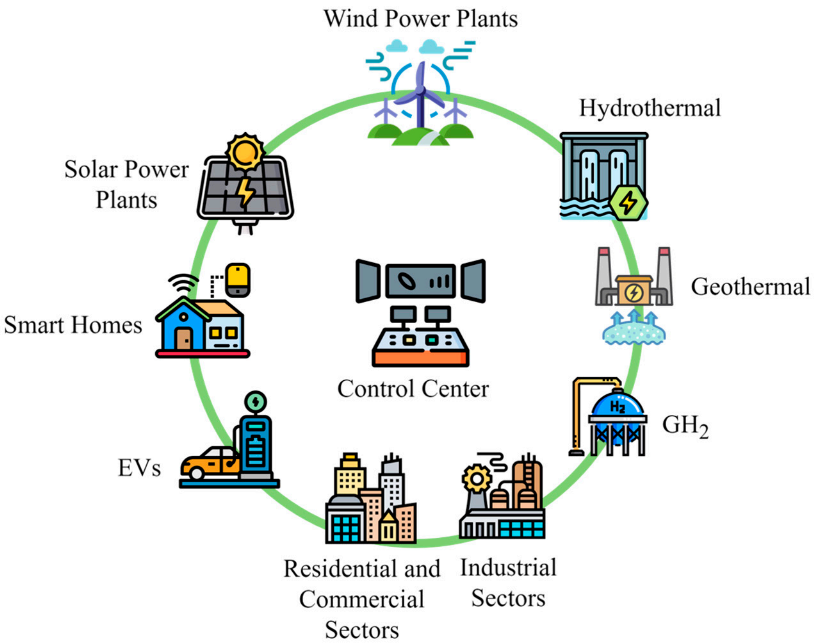

Figure 3. The overall concept of smart grids incorporating different sources/consumers.

As well as wind, hydropower, and geothermal energy generation, the production of green hydrogen (GH_2) is also represented, signifying its integration into the grid. The industrial sectors, situated at the bottom right, emphasize the distribution of energy to a variety of industrial applications, while the residential and commercial sectors situated in the bottom center represent the delivery of electricity to residences and businesses. The significance of EVs in the contemporary energy ecosystem is emphasized by their proximity to these sectors. Energy-efficient residences that are equipped with advanced technology are represented by smart homes, which are depicted to the left of EVs. The integration of solar energy is illustrated by the solar power facilities that are situated in close proximity to smart homes. The control center is the central element of the image, representing the location where information technology and power system networks converge to monitor and control the grid. The smart grid's efficient and reliable electricity services for both utilities and consumers are symbolized by the green circular line that connects all of these elements, ensuring a smooth flow of energy and communication.

The smart network has significant potential as the electricity grid becomes more complex and overloaded on a daily basis. The present energy demands are being challenged by the aging infrastructure [48]. Power outages are a significant concern during peak load hours, as demand frequently exceeds the supply capacity of the grid. Power infrastructures encounter a variety of issues at various levels, such as generation, transmission, and distribution [49]. At present, the majority of power facilities generate electricity using fossil fuels, which brings economic and environmental challenges to the power system [50,51]. In this regard, an analysis of the economic and environmental effects of smart grids has been conducted in [52], and they have presented their findings on variations in cost estimation in this field. The research recognized a shared component in the majority of definitions: the integration of digital processing and communication into the grid, which facilitates the maintenance of information management control and continuous data flow. Additionally, they observed that the analysis gap associated with uncertainties in environmental impacts and cost estimates could potentially produce more precise results. The optimal solution to the numerous issues encountered by power grids is the transformation of the electricity network into a smart grid, which is achieved by integrating the latest technologies with advanced equipment. Smart grids are designed to mitigate the environmental consequences of conventional power facilities by encouraging the utilization of renewable energy. The benefits of smart grid technology in assuring high energy efficiency, continuity of energy flow, and the security and stability of the power system are highlighted in the discussion of the development process [53,54]. The power grid is advanced by selecting the most suitable and reliable models from a variety of models that have been proposed for smart grids. The automation of the distribution network is important for the balance of supply and demand [55], and smart grid technology facilitates this process. This contribution eases load shedding during peak hours, which leads to a more efficient electrical network. As a result, smart grid technology is being developed to meet the current energy demands of the globe in a cost-effective and efficient manner [56–59]. Nevertheless, the implementation of smart grid technology is a multifaceted endeavor that presents numerous obstacles. To address this, a number of critical challenges associated with smart grids are described in [60], including issues related to measurement, sensing, information and communication technologies, control and automation technologies, energy storage, and power electronics. Overall, smart grid technology is designed to enhance the advantages for both utilities and consumers by delivering economic and reliable electricity services through the efficient use of available resources and advanced tools [61]. Consequently, the energy resources utilized in smart grids are reviewed in Figure 4.

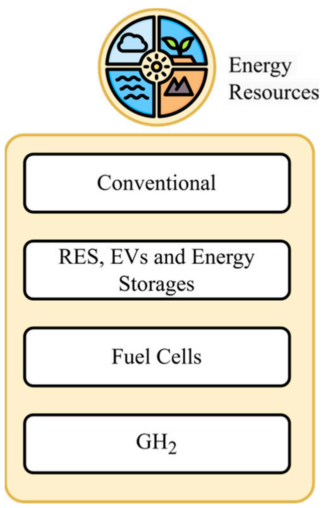

Figure 4. Energy resource classifications with some related works (Conventional [62–69], RES, EVs & Energy Storages [58,65,67–102], Fuel Cells [103–107], GH_2 [108–115]).

Supported by the concept of smart grids and the related energy resources, the advances and trends of energy processes are considered in four layers of energy generation, transmission, consumption, and storage that are shown in Figure 5.

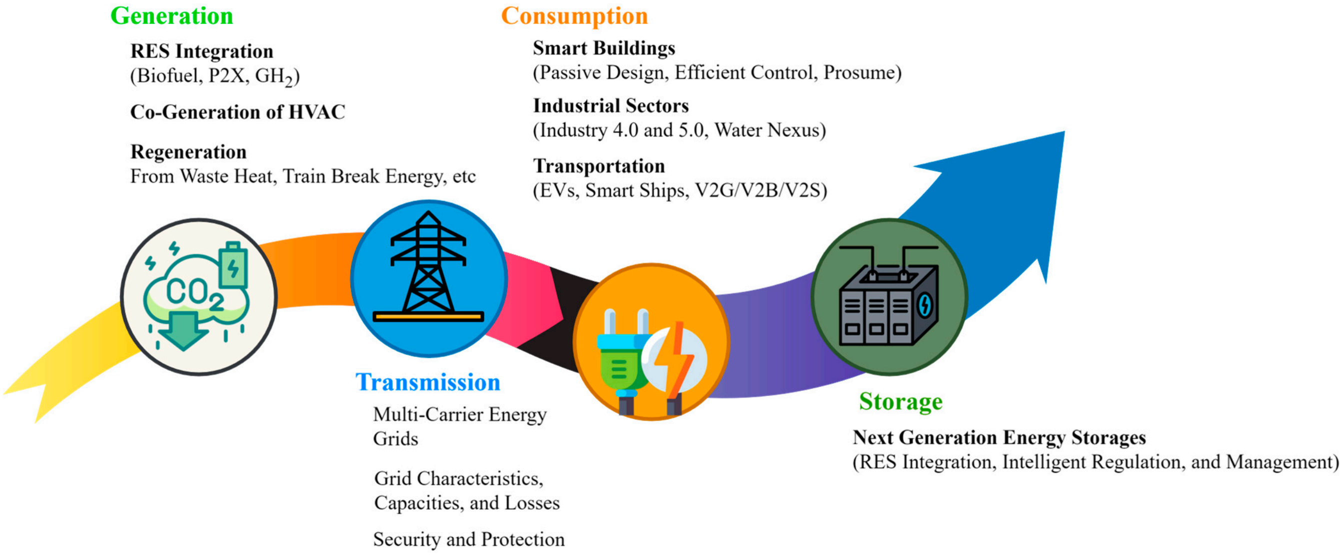

Figure 5. Layered trends and advances in EMS of smart grids. (vehicle-to-building /subway/grid (V2G, V2B, V2S)).

Generation: The process of decarbonizing energy generation includes the integration of RESs, cogeneration, low-carbon heating, and waste energy regeneration. Noussan et al. suggested that indicators such as the share of renewable energy, CO_2 emissions, and other pollutants can help compare power generation systems [116]. Bartłomiejczyk [117] highlights that vehicle movement and solar radiation are so variable they create uncertainty when assessing solar energy use for urban electric traffic. Biofuels derived from woody crops, agricultural residues, and waste materials [118] and electrofuels, made through power-to-gas and power-to-liquid technologies using RES electricity, also show potential as fossil fuel alternatives, especially for emergency diesel generators or heavy-duty vehicles. Co-generation systems increase overall efficiency, reduce the variability of renewable energy output, and create system reliability [119,120]. Combined heat and power (CHP) units in co-generation systems have a high share of RES, greater efficiency, and reduced emissions. District heating systems can save in energy by using low-temperature sources like seawater and groundwater, boosted by heat exchangers to raise temperatures, especially. Additionally, waste energy can be converted into usable power through regenerative processes. It was shown that the energy efficiency of urban subway systems, particularly in smart communities, could be enhanced using regenerative braking [121] by utilizing energy recovered from connected subway networks.

Transmission: Interconnected transmission networks, as illustrated in Figure 5 (second circle), highlight the multi-carrier energy systems potential in integrating distributed RES and enhancing urban energy sustainability. These systems facilitate the conversion and distribution of various energy forms, such as electricity, gas, heating, and ventilation, to meet diverse energy needs. According to [122], combining electric grids with district heating and cooling networks can increase the capacity for wind energy utilization and the share of urban energy demand met by solar power. The power-to-gas concept is also considered practical by converting excess renewable electricity into hydrogen gas through electrolyzers, which can then be injected into the natural gas infrastructure [123]. However, the operation of these networks must navigate technical and security challenges. For instance, ref. [124] reviewed ESS and control in mitigating the negative economic impacts of constraints on gas and power networks in power-to-gas systems. These constraints include limitations on hydrogen blending in natural gas pipelines and power line capacity. To address challenges in island wind power systems, particularly prolonged frequency fluctuations, ref. [125] presented a digital frequency relay control system proposed at network performance stabilization.

Consumption: The building, industrial, and transportation sectors are the urban energy primary consumers. Main strategies for creating low-carbon and zero-emission buildings include integrating sensors (such as occupancy, temperature, and water flow rate sensors), actuators (e.g., remotely controlled valves), and intelligent control algorithms, as well as reducing energy demand through passive design elements of thermal insulation, thermal mass, window placement, glazing types, and shading [126]. In recent years, the deployment of distributed energy resources (DERs) and demand response (DR) controls within energy systems [127,128] has shown an impact in lowering overall energy consumption, costs, and CO_2 emissions. By combining DERs with flexible building loads, peak demand can be reduced, and energy self-sufficiency can be improved. For instance, Ref. [129] implemented a MPC temperature control system in a building using dynamic pricing, peak trimming, demand-side management, and the smoothing of RES fluctuations. The industrial sector, when enhanced by Industry 4.0 and smart energy systems, can achieve high peak load reductions. A review by [130] demonstrated that digitalized industries can reduce energy consumption by applying flexible shutdowns and using inventory storage, all while maintaining operational efficiency. Water treatment plants are also considered important in smart grids due to the energy required for water production and distribution, particularly in arid regions. RES is increasingly being used for water desalination and stored in centralized reservoirs, resulting in sustainable urban development [131]. A mathematical model for the day-ahead economic dispatch of pumps and air blowers in wastewater treatment facilities is introduced by [132], ensuring compliance with particle concentration standards. In the transportation sector, which affects urban energy consumption and air pollution, cleaner and more efficient solutions are also important for future development. The transition to EVs is widely seen as a strategy for transportation decarbonization. According to [133], the smart grid framework can be applied to design future ships and port cities by integrating RES, ESS, and shore-side power systems. However, as noted by [134], the environmental benefits of EVs depend on the energy integration used to charge their batteries, as shown through life cycle assessments of EVs under current and future energy scenarios. Intelligent control algorithms are also being developed to optimize energy efficiency and service quality in transportation. These include systems for travel assistance [135], smart charging [136], V2G [137], V2B and vehicle-to-home (V2H) [138] applications.

Storage: The integration of RESs, network regulation, and efficient energy management is significantly influenced by ESS. The study [139] demonstrated that the integration of a CHP facility with thermal storage can result in a twofold increase in cost savings compared to flat pricing and a reduction in electricity and gas costs through storage arbitrage in DR programs, considering the fact that key characteristics of urban energy storage solutions include power rate, storage capacity, round-trip efficiency, response dynamics, cost, and spatial requirements, which are subject to significant variation. Designed to alleviate voltage fluctuations in a trolleybus supply system, The research, conducted in [140], introduced a battery buffer station. In recent years, the rise in EVs and the decreasing costs of electricity batteries have made them one of the most extensively adopted ESS technologies [141]. Also, the dynamics of thermal storage in communities are manifested by [142] given heating and cooling requirements. In cities that are seeking to achieve 100% renewable energy, hydrogen storage, which is facilitated by electricity-to-gas technologies [143], presents a considerable alternative for long-term and large-scale energy storage. The overall scheme of the EMS in smart grids is shown in Figure 6.

The objective of utilities is to mitigate superfluous expenditures by expanding their capacity to accommodate the perpetually rising demand for electricity. The effective utilization of existing energy resources is a critical approach to accomplishing this. Therefore, in order to regulate consumer energy consumption, utilities implement demand-side management (DSM) programs. In addition to augmenting reliability, DSM's primary objectives are to reduce electricity costs, improve social and environmental outcomes, and mitigate network issues. DSM programs comprise a variety of strategies, including energy efficiency initiatives, consumer load management (residential and commercial), and demand response. The objective of residential load management is to decrease electricity consumption and redirect peak demand to off-peak hours. Utilities have the ability to directly regulate residential charges; however, this method frequently generates privacy concerns that can impede its implementation. Rather than requiring load reductions, these challenges can be resolved by providing consumers with the option to reduce their electricity expenditures by managing their demand at various times of the day. In this alternative method, utilities implement variable pricing in response to fluctuations in demand. A two-way communication network is established when consumers receive regular updates on electricity prices via smart devices and modify their consumption accordingly. This converts conventional DSM into smart DSM, which ensures the efficient use of electricity at the distribution end, thereby fostering energy conservation. The application of ANN in industrial peak load management is the subject of [144]. Smart pricing schemes, in conjunction with HEM systems, also contribute to DSM by optimizing electricity consumption. Also, based on [19], several tools are being used in the EMS of smart grids and power systems, as denoted in Table 2. The mentioned tools can be integrated with AI models to proceed with advanced intelligent analytical abilities in the EMS of smart grids by analyzing the data exported from them.

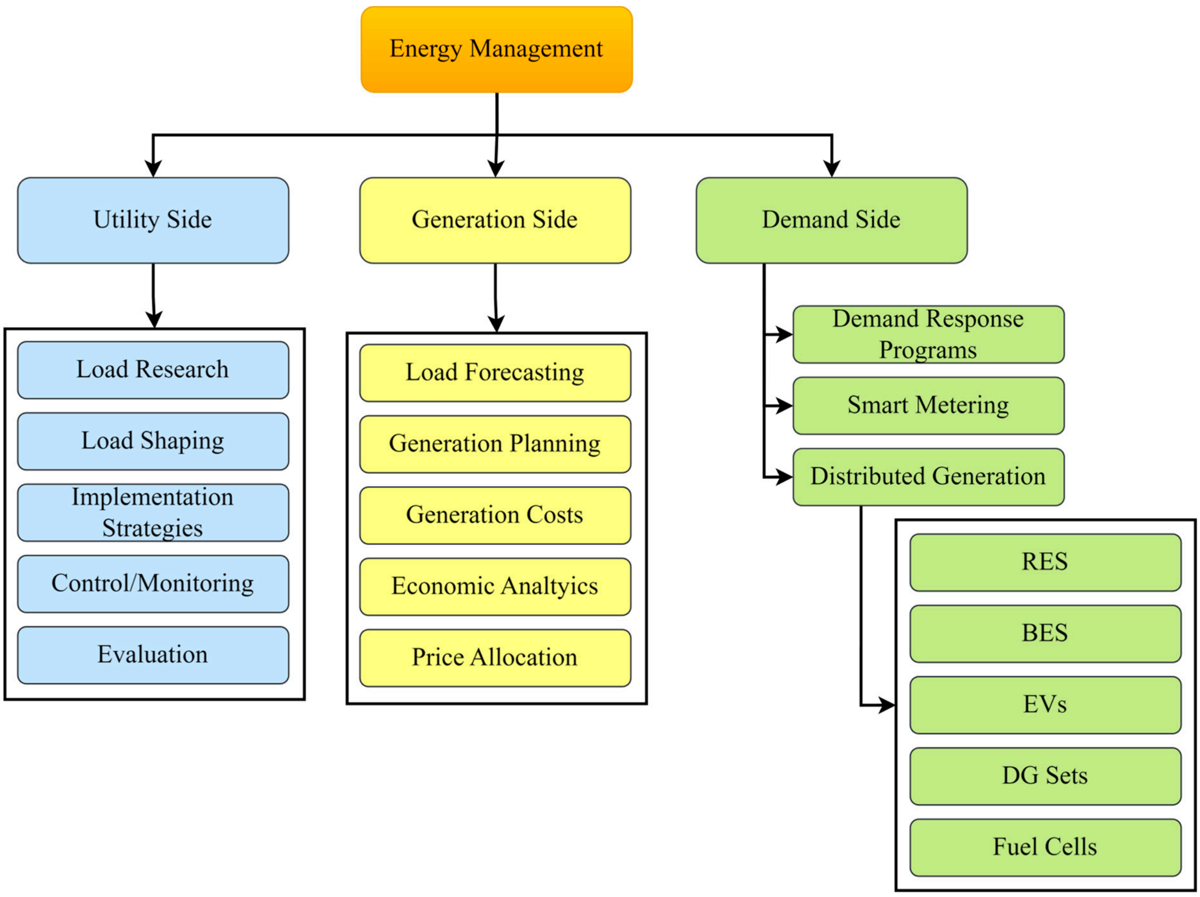

Figure 6. Overall classification of the EMS in smart power systems.

Table 2. Simulation tools used in optimal analytics of smart grids' EMS.

Simulation Tools	Objectives	Exemplary Application
MATLAB/SIMULINK	MATLAB is a computational software used in science and engineering such as modeling battery behavior, analyzing system performance, and developing control algorithms, including those for BES.	[145–156]
HOMER Pro	Simulation software to assess the economics and performance of microgrids, select ESS, evaluate RES, and optimize microgrids.	[157]
MAGNET–Infolytica	It facilitates the design and analysis of electromagnetic devices such as batteries, which assists in effectively optimizing BESS.	[158]
GAMS	The optimization modeling language is employed to address intricate issues in a variety of domains, such as BESS design. It provides optimization capabilities, flexible model formulation, and integration with other software tools.	[159]
PSCAD	The software is intended for the analysis of the dynamics and stability of electrical grids in the context of power system simulation.	[160–162]

MATLAB/SIMULINK is utilized to develop control algorithms for BESS, analyze system performance, and model battery behavior [145–156]. HOMER Pro evaluates RES, optimizes energy interactions of microgrids, selects ESS, and evaluates the economics and performance of microgrids [157]. MAGNET–Infolytica is dedicated to the optimization of effective BESS through the design and analysis of electromagnetic devices [158]. GAMS, an optimization modeling language, addresses intricate issues in a variety of domains, such as BESS design, by providing flexible model formulation and optimization capabilities [159]. PSCAD is employed to evaluate the stability and dynamics of electrical infrastructure in power system simulations [160–162].

3. Big Data Importance in EMS

Big data is instrumental in the transformation of smart power systems and their EMS, providing capabilities and insights to improve grid efficiency, reliability, and sustainability. Utilities can perform real-time monitoring and predictive analytics to anticipate and resolve potential issues before they escalate by leveraging vast amounts of data generated from diverse sources such as smart meters, sensors, and grid management systems. By optimizing energy distribution, demand forecasting, and the integration of RESs, advanced data analytics and ML algorithms minimize carbon footprints and reduce operational costs. Additionally, big data enables more effective demand response strategies and personalized energy services through comprehension of consumer behavior and energy consumption patterns, thereby facilitating improved decision-making. Big data will remain a fundamental component in the enhancement of the intelligence and resilience of modern energy infrastructures as the complexity of power systems increases. Consequently, big data can be considered in four sectors:

- Energy Provider.
- City and Building Construction Corporations.
- Investors.
- Authorities.

Energy providers and utilities must provide intelligent and appealing energy services as the energy sector becomes more competitive. By utilizing smart meter and sensor technologies, weather information, demographic data, and occupant feedback, it is possible to provide rapid feedback on the value of innovative pricing programs that are contingent upon customer utilization patterns. Consumer behavior toward energy efficiency can be altered, and intelligent home automation services can be enabled by user-centered applications that transform smart meter data into value for building occupants. Energy providers and utilities can enhance revenue recovery and reduce costs by optimizing data collection processes. Numerous environmental and climate assessment procedures (ECAPs) have been submitted by signatories to the Covenant of Mayors for Climate and Energy [163], a global initiative of cities and towns dedicated to transparent climate action, outlining their strategies for achieving long-term CO_2 reduction objectives [164,165]. Energy performance certificates must be collected by EU countries through the use of a variety of energy assessment instruments and procedures. Nevertheless, this data is frequently stored in multiple formats and dispersed databases, which requires a distinctive representation for cross-country and cross-domain analyses. Advanced energy services can be provided to specific beneficiaries, such as ESCOs, construction companies, and private proprietors, by integrating ECAPs and energy performance certificates with other data sources such as socioeconomic indicators and regulations. For example, insulation material manufacturers may discover valuable insights regarding the optimal marketing channels for their products. The heterogeneity of energy efficiency initiatives presents a challenge for investors and financiers in terms of scaling up investments. Nevertheless, the utilization of data for investment initiatives has the potential to enhance market confidence. Greater investment flows in energy efficiency can be stimulated by the availability of comparable, multilingual, anonymized historical data that has been collected from key buildings and industry segments. Initiatives for sustainable energy and climate planning must be spearheaded by local authorities and other organizations that are responsible for addressing long-term climate challenges. These entities can assess their carbon footprints and create exhaustive action plans that include a list of green energy interventions by collecting and integrating asymmetric data related to their operations and performance. Consequently, the whole process that big data can be utilized in EMS of power systems is manifested in Figure 7.

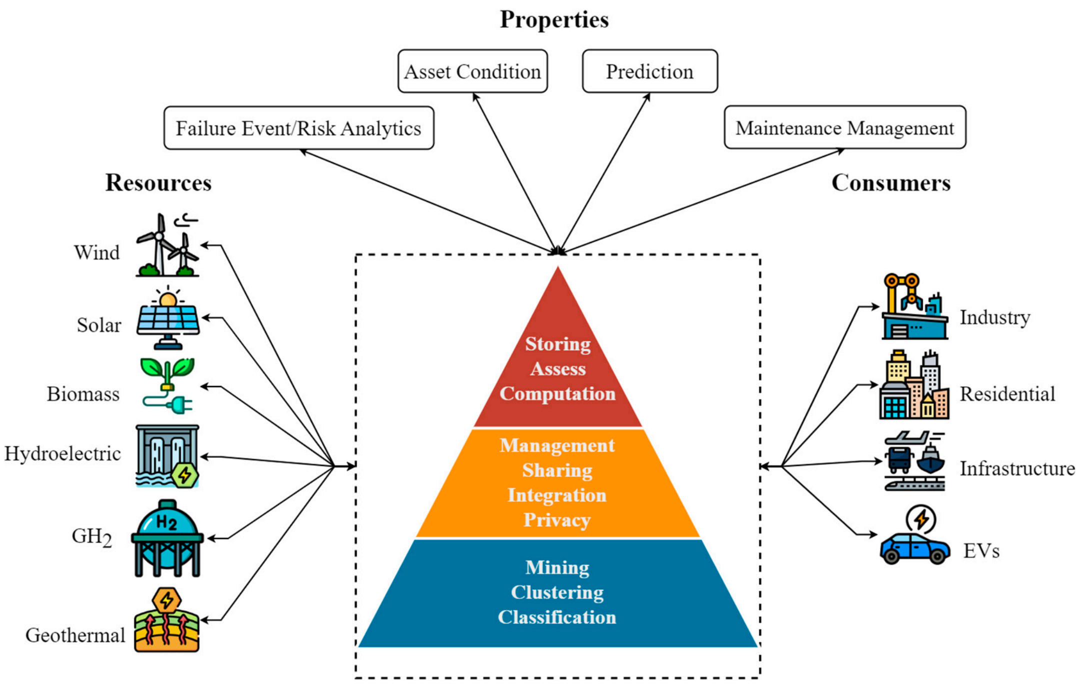

Figure 7. The overall usage of big data in smart power systems and their EMS.

The process is divided into three components, namely, resources, properties, and consumers (as indicated in Figure 7). These components are connected by a hierarchical pyramid that shows all of the data processing and management layers. Wind, solar, biomass, hydroelectric, GH_2, and geothermal energy sources comprise the available resources. Asset condition monitoring, prediction, failure event/risk analytics, and maintenance management are all included in the properties. Industry, residential, infrastructure, and EVs comprise consumers. The pyramid structure emphasizes three critical layers of data management: data storage, assessment, and computation at the summit; data management, integration, privacy protection, and sharing at the midpoint; and data mining, clustering, and classification at the base. This framework facilitates the optimization of energy distribution, the promotion of sustainability, and the enhancement of reliability in smart power systems, and it facilitates efficient data-driven decision-making. The data types and actions situated within the pyramid are the primary components of this process. It is partitioned into three primary layers, each of which represents a distinct degree of data processing and administration complexity. The primary objective of the uppermost stratum is to accumulate, evaluate, and process data.

Storing is the process of collecting and storing vast quantities of data that are derived from a variety of sources, including smart meters, sensors, and monitoring devices. Advanced algorithms and techniques are employed by computation to analyze the data, thereby converting unstructured data into actionable insights for decision-making. Organizational and operational aspects such as management, collaboration, integration, and privacy are addressed by the middle layer. Data management can organize and maintain data effectively, facilitating its accessibility for various applications. Collaboration is facilitated by data sharing, which enables the exchange of information between various entities and systems. Integration is the process of combining data from a variety of sources to produce a unified dataset that has a concept behind it. Data privacy preserves sensitive information from unauthorized access and assures regulatory compliance. To extract patterns, group similar data, and categorize information for predictive analytics and deeper insights, the base layer concentrates on mining, clustering, and classification, which are advanced data analytics techniques. Finally, the whole decision support and big data-driven EMS of smart grids are manifested in Figure 8.

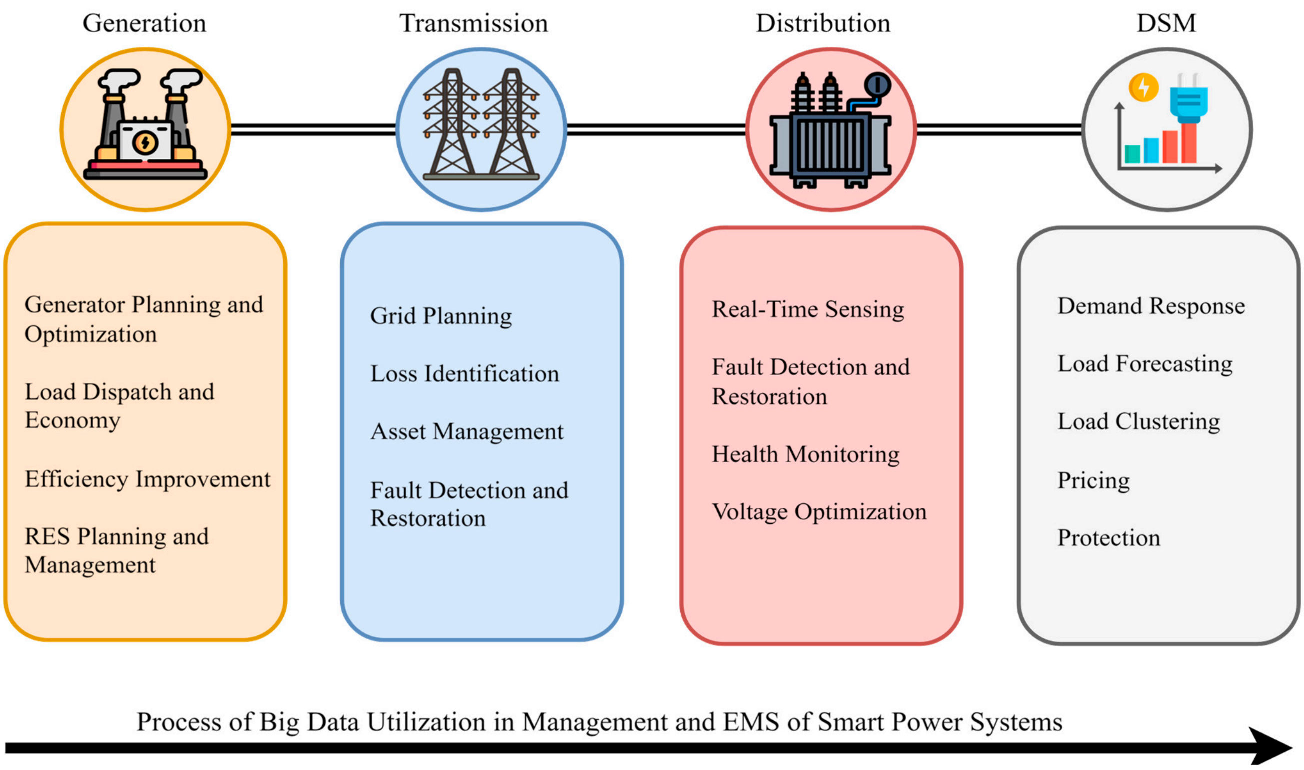

Figure 8. The decision process and EMS of smart grids using big data.

As shown in Figure 8, EMS of smart power systems is categorized into four primary areas:

- Generation.
- Transmission.
- Distribution.
- DSM.

Big data aids in the planning and optimization of generators, the dispatch and economy of loads, the enhancement of efficiency, and the planning and management of RES beginning with generation. In the transmission category, big data enables the efficient and reliable delivery of power by facilitating grid planning, loss identification, asset management, and defect detection and restoration. Real-time sensing, fault detection and restoration, health monitoring, and voltage optimization are all advantages of the distribution category, which improves the performance and resilience of the distribution network. Lastly, in the DSM category, big data facilitates demand response, load forecasting, load clustering, pricing, and protection, thereby allowing utilities to more effectively manage and respond to consumer demand, optimize energy consumption [166], and enhance the overall reliability of the system.

One of the big data types that is mostly used in power systems is considered geographical information system (GIS) data, which is an integral part of power system data. Relying on [167,168], the total amount of collected GIS big data is provided in Table 3.

Table 3. Amount of collected GIS big data of power systems by annual one million metering devices.

Collection	1/(day)	1/(1 h)	1/(0.5 h)	1/(0.25 h)
Records (billion)	0.37	8.75	17.52	35.04
Size (Terabyte)	1.82	730	1460	2920

Spatial and attribute data are the primary components of GIS data, which are used to describe the geographic characteristics of a particular region. Unique characteristics distinguish GIS data from other data types. Initially, they include a wide range of spatial data that illustrates the spatial distribution of these features besides the general data attribute of geographic features. Then, GIS is an advanced and large-scale system that employs a variety of data to characterize the environment and resources, resulting in an immense volume of information. Third, GIS data are not revised in real time; the GIS database typically has a lengthy update cycle. Herein, smart energy management can be substantially facilitated by GIS big data. For example, in a smart grid environment, GIS data layers can establish a correlation between electrical networks and geographical locations. Database integration is a critical component of energy big data analytics, as energy big data are collected from various sources using a variety of data acquisition devices. The data from different platforms and applications is frequently heterogeneous, independent, and mutually isolated, with varying structures, formats, and quality. Data integration is essential for the successful completion of numerous big data analysis duties. As a result, diverse models and methods for database integration have been indicated to resolve these challenges [169,170].

4. Artificial Intelligence and Machine Learning in EMS of Power Systems

Physical modeling and analysis are the primary methods employed in power system investigations. Nevertheless, these conventional approaches are unable to effectively address the increasing complexity and uncertainty of contemporary systems. As a result, AI techniques, which are capable of self-learning and necessitate minimal reliance on mathematical models of physical systems, present optimistic solutions [171]. Large volumes of data are typically managed by power systems as a result of the integration of a variety of components, including ESS, communication infrastructures, smart meters, EVs, and DERs. Traditional computational methods frequently fail to effectively manage and process this vast amount of data. Consequently, to effectively address these challenges, AI methodologies are implemented in power systems. Overall, the utilized classes of AI models in power systems [172] are illustrated in Figure 9.

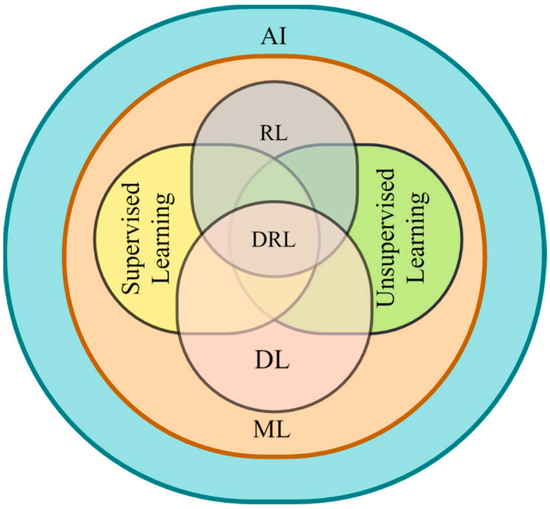

Figure 9. Overall AI classification.

AI, at its highest level, covers all technologies and approaches that strive to replicate human intellect. ML is a major subset of AI that stands out for its capacity to enhance its performance over time by learning from data without the need for explicit programming. ML can be classified into three main categories: supervised learning, where models are trained using labeled data; unsupervised learning, which involves identifying patterns in unlabeled data; and RL, which concentrates on training agents to make decisions by maximizing rewards in an environment. In this regard, Figure 10 presents different applications and optimization fields of AI in power systems.

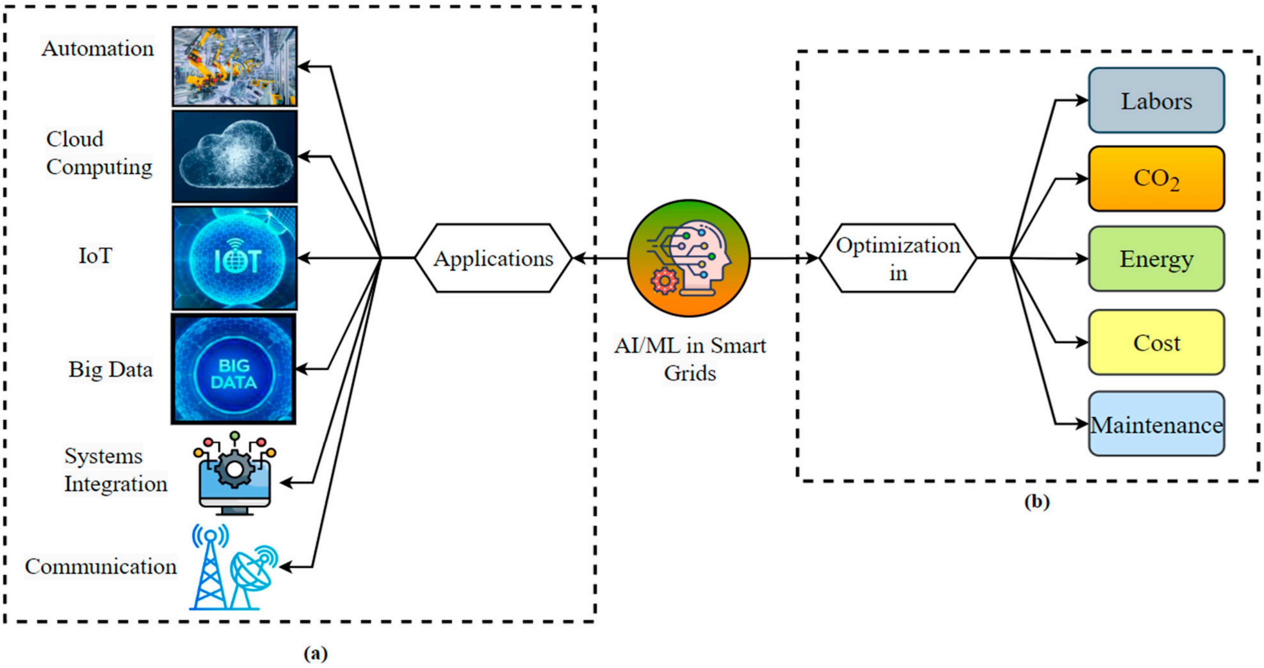

Figure 10. Overall (**a**) applications of AI in smart grids and (**b**) the related optimization targets.

As in Figure 10, AI in smart grids has been involved in several sectors, such as distributing workloads across many data centers to improve efficiency. Further, major studies have gone into reducing energy use and CO_2 emissions from power stations as well as maximizing the effectiveness of new conservation methods. But there is still an unexplored potential of IoT sensors and energy-saving strategies with RL. Energy costs are the largest portion of total production costs in modern industry. As a result, control over energy costs is an utmost priority for decision-makers. By employing AI/ML methods, data can be used to create mathematical models that ensure that machines are activated only when necessary, decreasing energy consumption. By moving operations to periods when energy prices are cheap, this method reduces the overall demand for consumption as well as delivers considerable savings. Moreover, decreasing consumption makes it easier to avoid operating additional power plants during peak demand periods so energy generation can remain at lower CO_2 emission levels. Therefore, since the importance and applications of AI/ML models are presented, the mostly used primary AI models and the power system are described, followed by Figure 11.

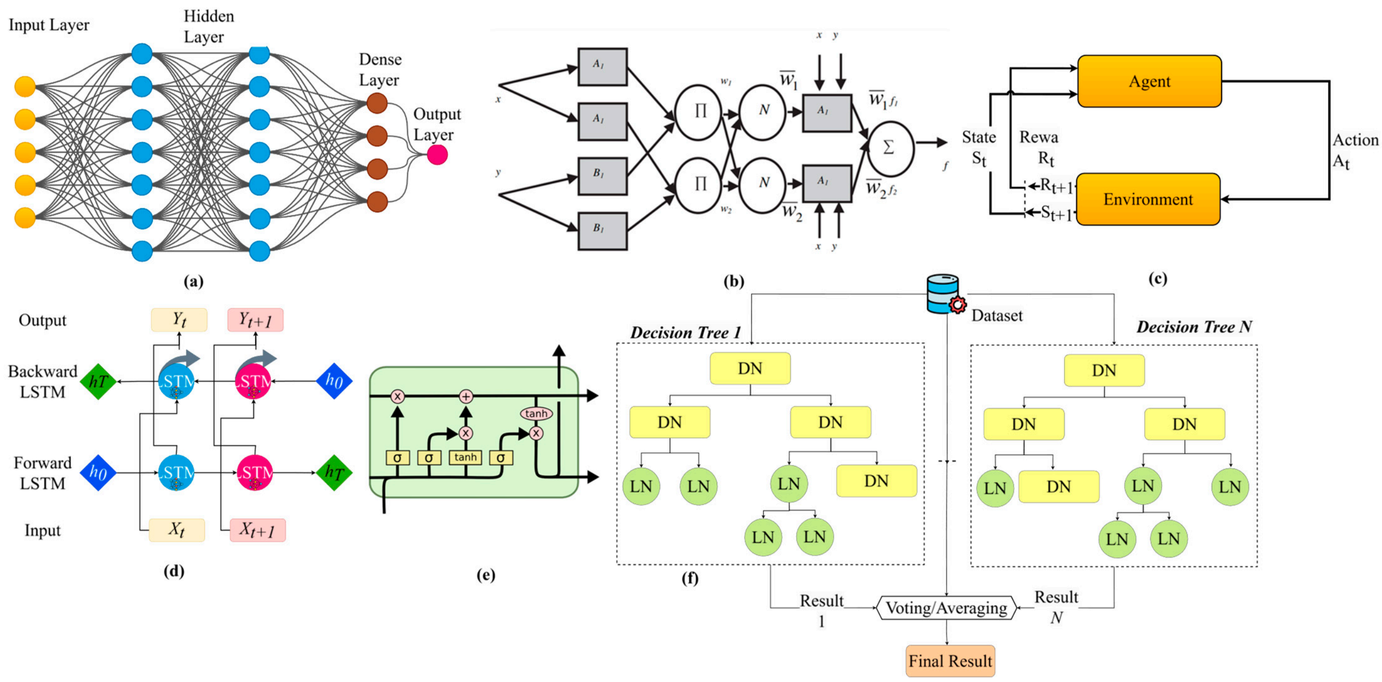

Figure 11. AI models of (**a**) Neural Networks, (**b**) Neuro-Fuzzy Logic [173], (**c**) RL, (**d**) BiLSTM, (**e**) LSTM, and (**f**) Decision Trees with Random Forest, where Y_t, X_t, h_T, and h_0 are the parameters of output, input, and hidden states at the index t and the initial hidden state, respectively. For the Neuro-Fuzzy, $[A_i, B_i]$ is the fuzzy set, W_i considered the network weights, as well as $[x, y]$ and f are the inputs and outputs, respectively. For the Decision Tree and Random Forest, *DN* and *LF* are the decision nodes and leaf nodes, respectively.

Neural networks that were first introduced in [174] are computational models appeared by the structure and function of the human brain (according to Figure 11). They are composed of interconnected layers of nodes or neurons that transmit and process information. Each neuron receives input, processes it using a weighted sum and an activation function, and subsequently transmits the output to subsequent layers. The architecture typically comprises an input layer, one or more concealed layers, and an output layer. Neural networks learn complex patterns and relationships within data by adjusting the weights of connections between neurons through a process known as training, which enables the network to minimize a loss function. Neuro-fuzzy systems [175] are hybrid computational models that capitalize on the advantages of both neural networks and fuzzy logic. These systems combine the interpretability and reasoning capabilities of fuzzy logic with the learning capabilities of neural networks, as shown in Figure 11b. A neural network structure that maps inputs to outputs is the typical component of a neuro-fuzzy system. The nodes represent fuzzy sets, and the connections represent rules. The fuzzy sets enable the system to manage imprecise and uncertain information by designating degrees of membership. The neural network then modifies these membership functions and rules through a learning process. This combination allows neuro-fuzzy systems to model complex, nonlinear relationships and provide human-readable rules. Their effective applications necessitate both adaptability and interpretability, such as control systems, decision-making, and pattern recognition. Regarding LSTM [176] and BiLSTM [177] (Figure 11d,e), the LSTM architecture is composed of memory cells and gating mechanisms including input, output, and neglect gates, which regulate the flow of information. This enables the network to retain pertinent information over extended periods of time. LSTMs are notably effective for tasks such as speech recognition, natural language processing, and time series forecasting due to this structure. By processing data in both forward and backward orientations, BiLSTM networks extend the LSTM architecture, thereby capturing context from both past and future states of the system. This bidirectional approach improves the model's capacity to comprehend the context and dependencies in sequential data.

As shown in Figure 11f, decision trees [178] are a form of supervised machine learning model that is employed for regression and classification tasks. They function by recursively partitioning the input data into subsets based on feature values, thereby establishing a tree-like structure of decision nodes and leaf nodes. The predicted outcome is represented by the leaf nodes, while each decision node represents a feature and a threshold. Decision trees are intuitive and accessible due to the tree structure, which enables the simple interpretation and visualization of decision rules. Nevertheless, they are not immune to overfitting, particularly when dealing with intricate datasets. Conversely, random forests are an ensemble learning approach that enhances the robustness and precision of decision trees. A random forest [179] is composed of a series of decision trees, each of which is trained on a random subset of the training data and a random subset of features. The final output is determined by aggregating the results, typically through majority voting for classification or averaging for regression after each tree independently classifies or regresses the input during the prediction period. This ensemble approach improves the model's generalization capabilities and performance on unseen data by reducing overfitting and variance. Random forests are extensively employed in a variety of sectors, such as finance, healthcare, and marketing, as a result of their adaptability and precision.

Regarding RL [180–182] (stated in Figure 11c), it is an ML paradigm that emphasizes the training of agents to make a series of decisions by interacting with an environment. In real life, an agent acquires the ability to accomplish an objective by executing actions and receiving feedback in the form of rewards or penalties. The agent's goal is to maximize the cumulative reward over time by utilizing known information and investigating the environment to make optimal decisions. Typically, Markov decision processes are employed to represent the learning process. In this model, the agent observes the current state, takes an action, and transitions to a new state, resulting in a reward. RL algorithms, including DRL, policy gradients, and Q-learning, employ a variety of techniques to approximate the optimal policy or value function. The capacity to learn from interaction and improve over time is essential in various disciplines such as robotics, game playing, autonomous vehicles, and recommendation systems where RL is applied, especially in power systems, as demonstrated in Figure 12.

Consequently, RL is mostly applied to buildings, markets, and the power grid. The buildings section emphasizes the role of RL in the optimization of multifarious building systems to improve occupant comfort and energy efficiency of buildings. This encompasses comfort illumination, which entails the adjustment of illumination levels to ensure that they meet comfort standards while simultaneously conserving energy. It is essential to manage temperature to ensure a comfortable indoor environment by effectively balancing the heating and cooling burdens. HVAC systems are managed to optimize thermal comfort and air quality while reducing energy consumption. The Indoor Air Quality aspect guarantees that the air within buildings is both safe and pure, taking into account factors such as ventilation and filtration. Finally, energy efficiency incorporates all strategies and technologies that are designed to decrease the overall energy consumption of buildings, enhancing their sustainability.

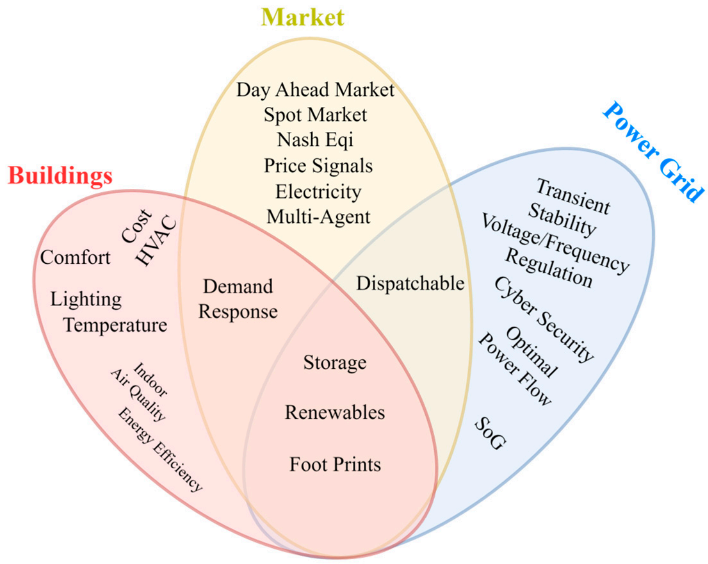

Figure 12. Applications of RL in EMS of power systems.

The market section includes the economic components of the energy system, where RL can be instrumental in optimizing market operations. The day-ahead market is a mechanism that enables market participants to offer and plan their operations by planning and trading electricity one day in advance. The spot market is a real-time market in which electricity is purchased and sold in accordance with the current supply and demand conditions. Nash equilibrium is a concept in game theory that describes a stable state in which market participants are unable to profit from unilaterally altering their strategy. RL can be employed to predict market behavior, identify optimal bidding strategies, and guarantee the stability and efficacy of market operations. Also, the electrical grid is a manifestation of the technical aspects of grid management, and RL has the potential to improve grid stability and reliability. The regulation of voltage and frequency is necessary to guarantee a consistent power supply by ensuring that they remain within permissible limits. Cybersecurity is essential for safeguarding the infrastructure from cyber threats and guaranteeing the integrity of data and control systems. The power system's capacity to endure and recuperate from short-term disturbances is referred to as transient stability. The optimal charging and discharging of ESS is contingent upon the administration of SoC. This ensures the longevity of the batteries and the reliability of the system. OPF is the process of determining the most efficient method of routing electricity through the grid to meet demand while minimizing losses and costs. Finally, on the side of dispatch as an act of operation in buildings, power grids, and its seen effect in the market, it is concerned with the optimization and management of energy resources in accordance with supply and demand conditions. The administration of ESS, which is essential for balancing supply and demand, is referred to as storage, particularly in the context of intermittent RES. Desalination emphasizes the incorporation of desalination processes, potentially utilizing surplus power for water purification. Price signals are the process of utilizing market price signals to make sound decisions regarding the allocation of energy resources as well as the optimization of costs and efficiency. The footprint manifests endeavor to reduce environmental and carbon footprints by employing efficient dispatch strategies.

Based on the information provided in Figures 11 and 12, AI/ML models have a similar initial process (according to Figure 13) and a difference in their application that requires dynamics or they are data-driven, which are manifested in Figure 14.

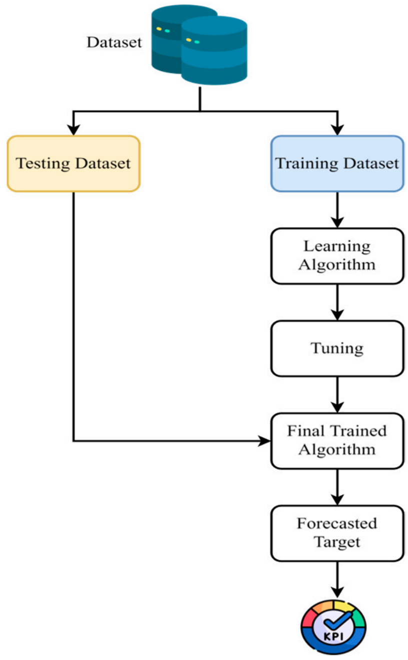

Figure 13. Two main steps of AI/ML-driven models.

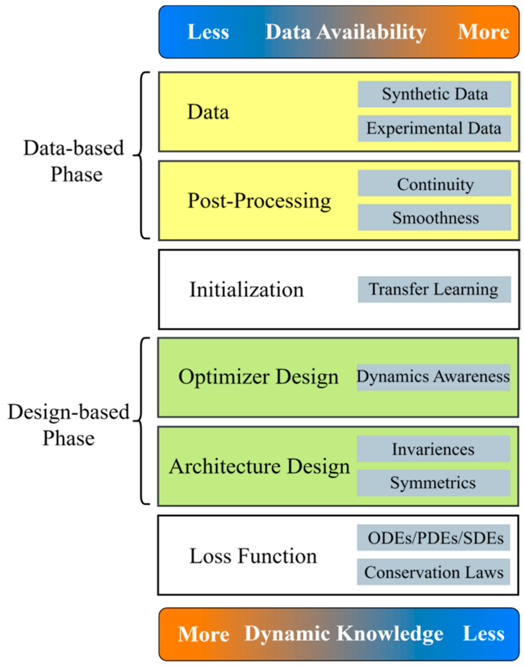

Figure 14. Data- and dynamics-based properties.

The dataset is partitioned into the following two unequal groups (Figure 13): the training dataset and the testing dataset, which correspond to the training and testing stages, respectively. The training dataset is employed to train the selected algorithm during the training phase. The efficacy of the trained algorithm is evaluated during the testing phase by utilizing the testing dataset. Supervised, unsupervised, and RL are the three categories into which ML problems can be classified. There is no single algorithm that can resolve all ML problems, as the classifications of these problems are of varying complexity and simplicity, necessitating the development of unique algorithms [183].

In Figure 14, it differentiates between synthetic data and experimental data by beginning with data. Synthetic data are frequently employed when real-world data are insufficient, and they are produced using established models or simulations. Experimental data are the actual observations that are acquired from experiments or real-world applications, and they serve as a solid foundation for the training of data-driven models. Techniques such as continuity and smoothness are indispensable for the refinement of model outputs during the post-processing stage. Smoothness is concerned with the elimination of noise and irregularities, which leads to more interpretable and reliable results, while continuity is achieved by ensuring consistency in the predictions. Methods such as transfer learning are the primary focus of initialization. This method enhances efficiency and performance, particularly when dealing with limited data by utilizing pre-trained models from related tasks. Transfer learning is instrumental in the adaptation of existing knowledge to new problems, thereby reducing the necessity for extensive data. Dynamics awareness is a component of optimizer design that presents the significance of comprehending the fundamental dynamics of the system being modeled. Models can more accurately predict and perform better by incorporating dynamic principles into the optimizer design, which allows them to better encapsulate the behavior of complex systems. Invariances and symmetries are integrated into the design of architecture. Symmetries assist in the reduction in complexity and the enhancement of generalization, while invariances guarantee that the model's predictions remain consistent under specific transformations. The design of model architectures that are both efficient and robust is guided by these principles. Finally, the loss function encompasses conservation laws and ordinary differential equations, partial differential equations, and stochastic differential equations (ODEs/PDEs/SDEs). The loss function can enforce physical constraints and conservation principles by incorporating these mathematical formulations, resulting in models that exhibit realistic behavior and adhere to known laws of nature.

In conventional power systems, the rotating bulk of synchronous generators serves as inertia. When the demand for electricity rises, these generators operate at a higher speed, while when it decreases, they operate at a lower speed. The frequency of the electrical grid is stabilized by this inertia. Furthermore, traditional systems can be dampened by regulating the generator's speed and dissipating energy when it operates at a non-synchronous speed. Inverters are the primary means by which RES technologies are typically connected to the grid. These inverters convert the direct current (DC) electricity produced by renewable sources into alternating current (AC) electricity. Inverters are unable to have the same level of stability to the power grid as synchronous generators due to their lack of inertia and damping properties. Additionally, the integration of renewable energy introduces disturbances and fluctuations in voltage and frequency, which present substantial challenges for power system control [184–186], as illustrated in Figure 15.

Consequently, it is imperative to implement an effective strategy for managing the integrity of power systems to facilitate the utilization of RES [187]. Nevertheless, the complex configuration of renewable power systems and the limited inertia of integrated renewable systems may render traditional linear or nonlinear control mechanisms ineffective in certain situations. Robust and adaptive control strategies have been implemented to mitigate the uncertainties introduced by RE. Robust controllers are intended to accommodate the most extreme worst-case scenarios, which frequently results in an excessively conservative design. Conversely, adaptive control methodologies necessitate precise parameter estimations and system models, which may prove difficult to acquire. AI-based generation-to-demand control techniques have been implemented to circumvent these constraints. The system's generation, transmission, distribution, demand, and energy storage components are all included in these techniques. The stability of RES-based power systems has been improved by the increase in the accuracy of fault diagnosis and detection, which is a result of the effective management of uncertainties by AI algorithms [188,189].

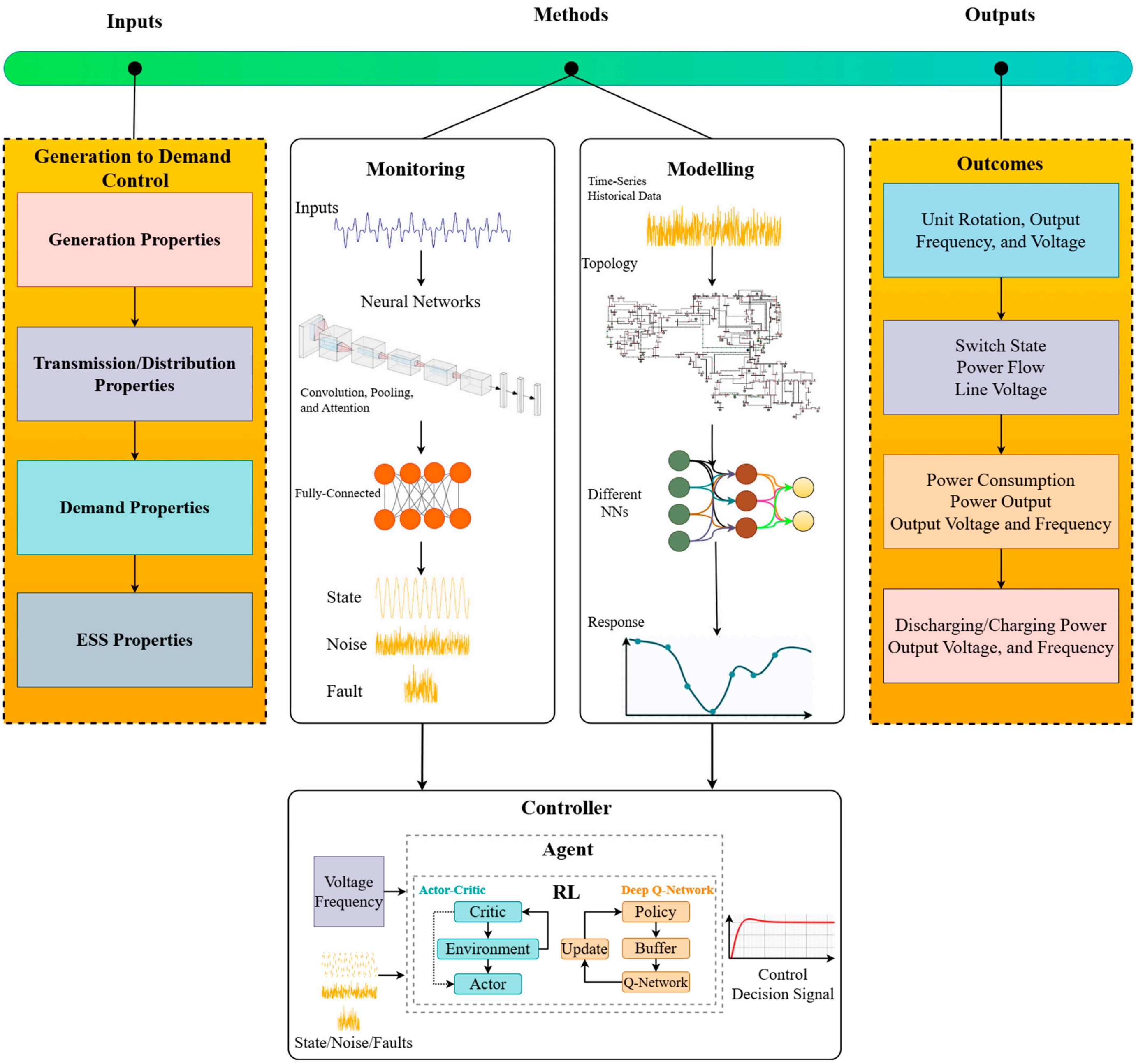

Figure 15. AI control concepts for RES.

4.1. Generation

A challenge to the operational stability of power generators is introduced by the inherent uncertainty of RES. The power output is subject to substantial and unpredictable fluctuations due to the intermittent and variable nature of resources such as solar and wind. In the event of a sudden decrease in RES output [190], grid administrators may be required to promptly implement control measures to bring additional generators online and maintain a consistent power output. The nonlinear characteristics and noise introduced by RES generators frequently present a challenge for traditional linear control principles, such as proportional–integral–differential control (PID) [191,192], leading to unsatisfactory dynamic performance. AI-based control mechanisms have garnered attention for power system control [193], particularly for systems with high integration of RES.

One method of guaranteeing the stability of power systems is to directly regulate the output frequency of RE generators. For example, the excitation current in the field winding can be adjusted to manage frequency deviations in the power output of wind turbines and regulate rotor speed. The magnetic field surrounding the rotor is fortified by increasing the excitation current, which in turn increases the rotor's speed to align with the grid frequency [194]. Nevertheless, a secondary frequency decline in the power system [195] may result from the recovery of rotor speed when the excitation current is reduced. To regulate the frequency of wind power, intelligent algorithms [196], dynamic (multi-agent proximal policy optimization), as well as data-driven [197], and actor-critic RL [195,198] are implemented with an emphasis on the mechanical and electrical characteristics of wind turbines and their coupling relationships. Attention mechanisms monitor defects and noise in the power system, while RL-based algorithms (such as multi-agent proximal policy optimization and actor-critic) make decisions and send control signals. The electrical characteristics of wind turbine blades, towers, and drivetrains are influenced by their properties, which indirectly affect the output frequency. This phenomenon is challenging to simulate using conventional control methods. Nevertheless, AI-based controllers can identify and integrate these relationships to precisely regulate wind power frequency by processing complex high-dimensional state spaces and extracting information [199].

Inverters [200,201] regulate the output power frequency, as photovoltaic solar cells do not have rotors, as opposed to wind turbines. The transient frequency of inverters is influenced by a variety of factors, including solar irradiance, which presents a challenge for conventional controllers due to its uncertainty. To account for these factors when making decisions and transmitting control signals, AI-based controllers can integrate them into the state space. AI methods are particularly adept at extracting information from intricate, high-dimensional data and analyzing the complex relationships between output frequency and other variables. As a result, control signals for solar photovoltaic devices have been generated using AI-based controllers, including PSO, random forest regression, attention-enabled multi-agent DRL [202], and ANN [203], to modulate their output frequency.

Voltage regulation is nearly as essential as frequency regulation in the pursuit of power system stability [204,205]. The low inertia of power electronic inverters that are employed to connect RESs to the grid can result in voltage fluctuations as a result of the uncertainty associated with RESs. RNNs [206], RL [207], and DRL [208] are among the AI-based techniques that can generate optimal control strategies and implement real-time voltage regulation, some based on dynamics, and some based on the pre-trained frameworks, to mitigate the adverse effects of this uncertainty. These methods utilize data from sensors and monitoring devices, including voltage, current, and power measurements. This information assists controllers in obtaining a comprehensive understanding of the conditions of devices, including inverters and wind turbines, to make more informed decisions, generate more effective control signals, and improve the stability of the renewable power system.

AI algorithms or their combinations are selected to regulate the voltage or frequency, in terms of system stability, that is generated based on factors such as the scope of the problem, the complexity of the problem, and the action space. The low-dimensional action space of heuristic algorithms can render them effective in straightforward scenarios such as the control of a single wind turbine. Nevertheless, DRL-based control algorithms are more appropriate for complex systems such as hybrid power generation systems with larger-scale RES. DRL algorithms, relying on the dynamics of the system, are particularly adept at learning optimal policies in continuous action spaces and exhibiting resilient learning capabilities in high-dimensional state and action spaces. Consequently, these methodologies are well suited to the inherent complexity of large-scale RES-dominant power systems.

4.2. Transmission and Distribution

Power delivery encompasses two critical phases, namely, transmission and distribution. Distribution is the process of converting high-voltage power to lower voltages that are appropriate for end-users such as homes and businesses, while transmission involves the bulk movement of power over long distances at high voltages. The primary cause of voltage and frequency fluctuations in transmission and distribution is the imbalance between electricity generation and consumption. Voltage reductions occur when demand exceeds supply, which occurs when RES output decreases from its expected amount. In contrast, voltage surges may result from low demand and a high-RES penetration output. The rotation speed of generators is influenced by the balance between generation and consumption, resulting in frequency variations. To regulate these fluctuations and preserve the stability of the power grid, a variety of devices are implemented, including capacitor banks, on-load tap converters, and tap-changing transformers.

To guarantee the stability of RES-dominant power systems [209], voltage and frequency must be maintained throughout the power transmission and distribution. Linear control principles are employed in conventional control methods to ensure system stability. Nevertheless, the complexity of power transmission and distribution systems in renewable power systems is a result of the variability of RESs and the necessity of constructing new transmission lines to connect remote RESs to the grid. Accurately establishing response functions for voltage and frequency regulation in these systems is a difficult task. As a result, neural networks, including attention-based models [210] and their alternatives [211], are employed to approximate the relationship between the output voltage and frequency and the condition of the RES-based power system, including wind velocity, solar irradiance, and ESS integration. Attention mechanisms have also been employed to monitor the transient states of voltage and frequency in transmission and distribution systems and to adapt response models [212,213]. Accurate system models are developed through the utilization of high-quality historical data in these methodologies. Nevertheless, the acquisition of specific information from the power transmission and distribution system can be difficult, particularly in low-probability extreme scenarios involving RESs or newly constructed RES farms where there may not be enough historical data to train neural networks.

To circumvent the necessity for precise system models, model-free control strategies like DRL-based algorithms have been implemented to regulate voltage and frequency. These strategies are capable of adapting to system variations and uncertainties by learning control techniques from environmental interactions and experiences. These individuals are well-suited to managing intricate systems due to their capacity to learn response models efficiently. In single-agent DRL [214,215], a single AI-based control device is trained on historical data to generate control signals (as the masters) for transmission and distribution devices (as the slaves). In contrast, multi-agent DRL assigns agents with individual reward functions and coordinates them to obtain improved control results [216–219]. The utilization of multiple agents enhances the scalability, representation of system dynamics, and coordination of distributed decision-making for voltage control [220]. Nevertheless, the applicability of this multi-agent approach may be diminished as a result of the potential for privacy concerns to arise during data transmission and the resulting increase in communication overhead and computation time. The introduction of distributed DRL has been made to minimize communication overhead by training agents locally without transmitting data to a centralized server. However, privacy concerns persist. Another method to mitigate privacy concerns is DRL [221], and federated learning (FL) [222], which involves the training of multiple agents without the direct transmission of raw data. Nevertheless, this method is still time-consuming. Attention mechanisms can be integrated into DRL frameworks to expedite agent training; however, these algorithms are not interpretable in decision-making, which complicates the explanation of the fundamental reasoning and logic behind control strategies. For example, federated DRL can accomplish decentralized voltage regulation; however, the data characterization and decision-making mechanisms are not interpretable.

Model-based algorithms have a precise and efficient method for the development of control strategies for transmission and distribution; however, they necessitate precise system models. In contrast, model-free algorithms are more appropriate for complex, large-scale, or highly uncertain systems that necessitate adaptability and robust approximation capabilities, despite the fact that they may require additional training time and provide limited interpretability. In practice, the selection of an algorithm should be determined by a thorough assessment of the problem's unique characteristics and requirements.

4.3. Electricity Demand

The traditional method of regulating voltage and frequency in power systems is to modulate generators to maintain system stability. Nevertheless, the availability of conventional power facilities that are capable of participating in frequency and voltage control will decrease as the proportion of RESs increases. As a result, the stability of RES power systems are becoming more dependent on flexible load demands, which are able to be altered or shifted in response to changes in the power system.

Conventional control methods are insufficient for the preservation of power system stability due to the complexity and diversity of flexible load demands [223]. Rather, AI techniques are implemented to regulate a variety of flexible burdens. For example, various AI techniques, including DRL [224,225], and neural networks alternatives [226], have been suggested as approaches for managing the charging of EVs. These AI-based control mechanisms strategically manage charging to accomplish load–demand balancing by analyzing historical and real-time data to capture charging demand and grid load trends. Furthermore, AI control mechanisms have the capacity to learn and optimize autonomously, thereby refining their control strategies over time. This improves the power system's response capabilities and enhances comprehension of it.

Consequently, to balance power supply/demand, AI techniques such as multi-agent methods [227], different types of RL [228–230] are also implemented to manage other flexible load demands, including electric water heaters and HVAC systems. These control mechanisms, which are AI-based, engage with a variety of RES power systems and adaptable loads to continuously optimize control strategies.

Demand-side control, which involves requesting that consumers modify their electricity consumption, has not been extensively implemented due to consumers' potential reluctance to engage in demand regulation. To resolve this issue, it is imperative to conduct additional research on incentive mechanisms to enhance consumer interest in participating in initiatives related to this dynamic.

Numerous AI-based algorithms exist for managing flexible loads in renewable power systems, each with its own individual advantages and disadvantages. Heuristic algorithms are particularly effective in problems with substantial search spaces; however, they may be inefficient for real-time load requirements. DL-based control algorithms are capable of effectively managing complex tasks and large-scale data, rendering them appropriate for flexible load control. Conversely, they may encounter challenges in terms of inadequate data accessibility or inadequate explanatory capabilities. DRL algorithms combine the advantages of DL and RL, providing improved adaptability and flexibility for flexible load demand control. Real-time learning and decision-making are enabled by these algorithms, which acquire optimal decision-making strategies through interaction with the environment without the necessity of extensive labeled training data. Consequently, dynamically changing demands can be accommodated by DRL techniques, which can also manage real-time flexible load control duties. However, the training and optimization of DRL-based algorithms can be resource-intensive and time-consuming, and they may experience stability or convergence issues when managing complex problems.

4.4. Energy Storage System (ESS)

The integration of ESS into RES-dominant power systems has been identified as a viable measure for reducing the operational risks associated with the inherent uncertainty of RESs [231,232]. These systems can ensure the system's stability by providing virtual inertia and damping, acting as power supplies during high-demand periods, and storing surplus energy during off-peak periods. Traditional control principles such as the bang-bang control principle necessitate precise system models and are unable to effectively address the cacophony and disturbances in the power system that RE introduces. The real-time responsiveness of controllers for ESS can be improved through the use of AI-based techniques. As an example, adaptive fuzzy neural networks [233,234] have been implemented to regulate the operation of ESS by serving as a virtual synchronous generator within the power system. To compensate for the low inertia and inadequate damping capabilities of renewable power systems, neural networks are employed to adaptively modify the parameters of the virtual synchronous generator, including the charging and discharging power of the system. Additionally, RL-based different strategies [235–237] have been employed to develop and operate power system controllers, which encompass various forms of ESS.

The establishment of response models is facilitated by the precise prediction of voltage and frequency fluctuations in renewable power systems by DL algorithms. These models can be further improved through the use of techniques such as MPC. Nevertheless, the scale of DL algorithms' networks may result in latency issues when applied to real-time control tasks as they necessitate a significant amount of labeled training data and computational resources. Conversely, DRL-based algorithms offer adaptable and flexible control for ESS. DRL algorithms are capable of managing the inherent variability and uncertainty in renewable power systems by learning control strategies through interaction with the environment. DRL is well-suited for real-time control tasks due to its adaptability, despite the potential challenges associated with computational demands and training time. Additionally, Refs. [238–243] considered the chance-constrained models in EMS and control of power systems, as well as their integration with IoT, ESS, and hubs.

Finally, the presented different fundamental models are compared based on their robustness, dynamics requirements, cloud-based control abilities, and computational complexity in Table 4 and Figure 16.

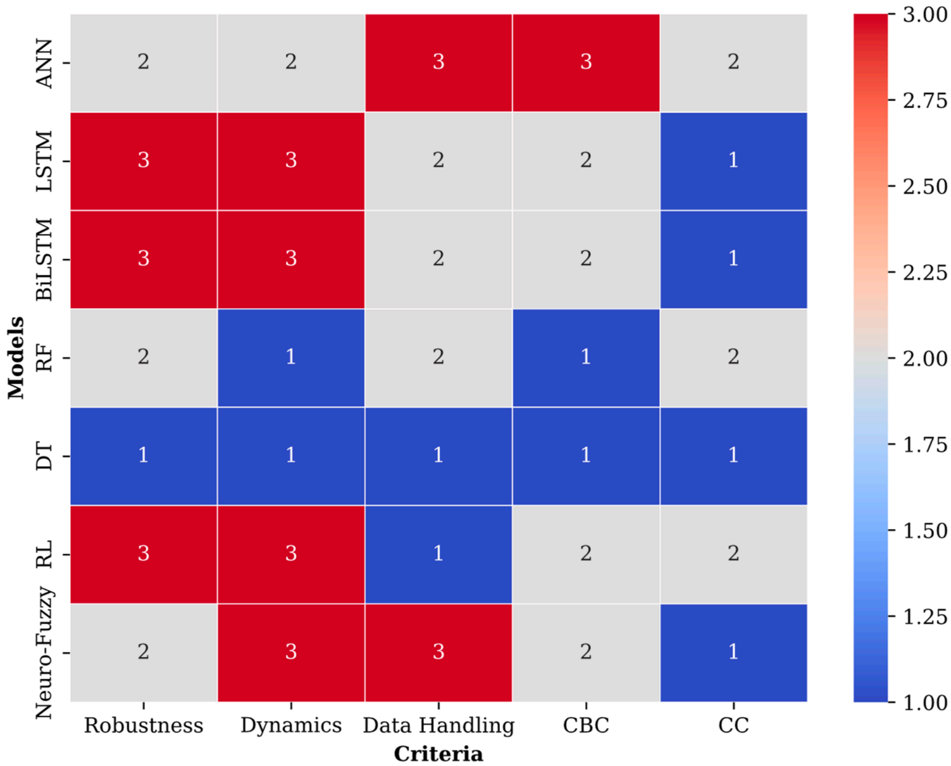

Figure 16. Correlation of the models' requirements with their criteria in the EMS of power systems, as 3 = ✪✪✪, 2 = ✪✪✪, and 1 = ✪✪✪.

Table 4. Comparative properties of different AI models.

Algorithms	Robustness	Dynamics	Data Handling	Cloud-Based Control	Computational Complexity
ANN	☆☆★	☆☆★	☆☆☆	☆☆☆	☆☆★
LSTM	☆☆☆	☆☆☆	☆☆★	☆☆★	☆★★
BiLSTM	☆☆☆	☆☆☆	☆☆★	☆☆★	☆★★
RF	☆☆★	☆★★	☆☆★	☆★★	☆☆★
DT	☆★★	☆★★	☆★★	☆★★	☆★★
RL	☆☆☆	☆☆☆	☆★★	☆☆★	☆☆★
Neuro-Fuzzy	☆☆★	☆☆☆	☆☆☆	☆☆★	☆★★

Superior: ☆☆☆, Intermediate: ☆☆★, Inferior: ☆★★.

LSTM and BiLSTM are more robust than ANN and Neuro-Fuzzy in terms of robustness, as they are capable of effectively managing long-term dependencies and sequential data. However, they may be less robust in chaotic conditions. DTs are inferior due to their propensity to overfit, while RF is intermediate, benefiting from its ensemble approach. Continuous learning and adaptation are the hallmarks of RL, which is distinguished by its robustness. LSTM, BiLSTM, and RL are superior in terms of dynamics as they are capable of effectively managing complex temporal and dynamic environments. In contrast, RF and DT are inferior as they struggle to handle dynamic data. LSTM and BiLSTM are effective with sequential data, while ANN and Neuro-Fuzzy excel with diverse data types in data handling. RF is capable of effectively managing structured data, whereas DT and RL are less well-suited for direct data processing. In terms of cloud-based control, ANN is the most effective, followed by LSTM, BiLSTM, and Neuro-Fuzzy, which are also deployable but have variable resource requirements. The efficiency issues of RF and DT render them less suited for cloud applications. Finally, in terms of computational complexity, RF and RL are intermediate with a manageable complexity, whereas ANN is also intermediate but can become complex when used with deep networks. The advanced processing requirements of LSTM, BiLSTM, and Neuro-Fuzzy render them more complex.

4.5. Key Performance Indicators (KPIs)

KPIs are indispensable metrics that evaluate the efficacy and efficiency of ML models in EMS within power systems. These indicators are essential for assessing the effectiveness of these models in predicting, optimizing, and managing energy consumption and distribution. For example, the predictive performance of models utilized in demand forecasting is evaluated using metrics such as precision, recall, accuracy, and F1-score. Operational efficiency can be assessed by comparing the ratio of energy output to input, which assists in identifying areas where energy usage can be optimized. The power supply is guaranteed to remain stable and uninterrupted by reliability indicators, including system availability and failure rates. Moreover, KPIs that are associated with cost, such as cost savings from optimized energy use, present tangible financial benefits. By consistently monitoring these KPIs, stakeholders can make informed decisions to improve the performance of EMS, resulting in more sustainable and cost-effective energy management. KPIs, including minimum absolute error (MAE), mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), root mean square percentage error (RMSPE), F1-score, accuracy, recall, precision, computational complexity, and ranked probability score (RPS), are essential for assessing the performance of ML models in EMS. The average magnitude of prediction errors is quantified by the MAE, which has a clear indication of accuracy. RMSE and MSE accentuate larger errors as a result of their squared nature. RMSE is more interpretable as it is expressed in the same units as the target variable. MAPE and RMSPE are percentages that convey prediction errors, providing information on the relative size of errors. The F1-score is a critical metric for classification tasks within EMS as it balances precision and recall, indicating the model's ability to identify true positives. Accuracy is a metric that quantifies the percentage of correct predictions, whereas recall and precision are concerned with the totality and accuracy of positive predictions, respectively. The model's efficacy in terms of time and resources is evaluated by computational complexity, which ensures the feasibility of real-time applications. In ambiguous scenarios, the RPS enhances decision-making by assessing the accuracy of probabilistic predictions. Consequently, the mentioned KPIs are mathematically defined in [244–247].

5. Challenges Ahead

Integrating AI into EMS can enhance the efficiency, reliability, and sustainability of energy systems. However, the process is not without challenges. Implementing AI in domains such as smart grids, distribution networks, EVs, buildings, and fault detection requires intricate interactions between technology, infrastructure, data, and human factors. One key challenge is data quality and availability, as energy systems often have incomplete or noisy data, though improved sensor technology and IoT devices can address this issue. The complexity of energy systems with multiple stakeholders and diverse energy sources also poses a challenge, which can be tackled by advanced AI algorithms like multi-agent systems or deep learning techniques. Moreover, integrating AI with legacy energy infrastructures demands the development of adaptive interfaces and middleware. Cybersecurity is another concern as AI introduces new vulnerabilities requiring secure AI models and robust cybersecurity frameworks. Lastly, AI's computational demands, especially for deep learning, can be limiting in real-time applications, a problem that can be mitigated by more efficient algorithms, cloud computing, and edge computing technologies. Addressing these challenges is essential to fully harness the potential of AI in energy management and ensure efficient as well as secure operations in real-world systems.

6. Future Perspectives

The future prospects of AI in this industry are vast, including decentralized energy management and improved decision support systems, all of which aim to create more efficient, durable, and environmentally friendly energy systems capable of meeting modern demands and supporting the global shift towards RESs. AI will facilitate decentralized EMS, enabling efficient and resilient energy distribution through microgrids and DERs. It will also drive real-time optimization, balancing supply and demand more effectively while reducing energy waste in smart grids and buildings. AI-based predictive maintenance and fault detection will reduce downtime and maintenance costs by forecasting equipment failures before they occur, significantly enhancing the reliability of energy systems. Furthermore, AI will be key in managing the variability of RESs, ensuring stable and efficient grid integration. Smart buildings and cities will benefit from AI-driven EMS that autonomously manages energy consumption and climate control, contributing to urban sustainability. Regarding EVs, AI will optimize performance by managing operating conditions and predicting degradation, which further promotes their adoption. Human-AI collaboration will evolve with AI handling complex optimization tasks while human operators focus on strategic decision-making. As AI technologies become more sophisticated and affordable, global adoption will scale, fostering a more sustainable and efficient energy sector. Finally, AI-enhanced decision support systems will empower operators with more informed decisions on energy production, distribution, and consumption, driving better decision-making in EMS.

7. Conclusions

The proposed review study has conducted an analysis of the important impact of AI and ML on the development of new EMS. Through a comprehensive analysis of more than 240 publications, this research has presented an in-depth review of the incorporation of AI and ML in many areas of EMS. These areas include forecasting, fault detection, electricity markets, optimizing buildings, and enhancing EV technology. Incorporating big data into EMS is important for improving the efficiency, reliability, and scalability of these systems. Nevertheless, this paper also highlights some of the challenges that still exist, including the necessity for advanced algorithms, the intricacy of data administration, and the need for defined protocols. These challenges highlight the need for ongoing study and improvement in this sector. The future of AI and ML in EMS has potential with the ability to develop EMS methods through innovative advancements. The study presents a future-oriented viewpoint, proposing that addressing the existing constraints could result in a more green energy system driven by cutting-edge AI and ML technologies.

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References

1. Perera, A.; Kamalaruban, P. Applications of reinforcement learning in energy systems. *Renew. Sustain. Energy Rev.* **2021**, *137*, 110618. [CrossRef]
2. Akhtar, S.; Bin Sujod, M.Z.; Rizvi, S.S.H. An Intelligent Data-Driven Approach for Electrical Energy Load Management Using Machine Learning Algorithms. *Energies* **2022**, *15*, 5742. [CrossRef]
3. Entezari, A.; Aslani, A.; Zahedi, R.; Noorollahi, Y. Artificial intelligence and machine learning in energy systems: A bibliographic perspective. *Energy Strat. Rev.* **2023**, *45*, 101017. [CrossRef]
4. Mosavi, A.; Salimi, M.; Ardabili, S.F.; Rabczuk, T.; Shamshirband, S.; Varkonyi-Koczy, A.R. State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. *Energies* **2019**, *12*, 1301. [CrossRef]
5. Ghoddusi, H.; Creamer, G.G.; Rafizadeh, N. Machine learning in energy economics and finance: A review. *Energy Econ.* **2019**, *81*, 709–727. [CrossRef]
6. Rosero, D.; Díaz, N.; Trujillo, C. Cloud and machine learning experiments applied to the energy management in a microgrid cluster. *Appl. Energy* **2021**, *304*, 117770. [CrossRef]
7. Musbah, H.; Aly, H.H.; Little, T.A. Energy management of hybrid energy system sources based on machine learning classification algorithms. *Electr. Power Syst. Res.* **2021**, *199*, 107436. [CrossRef]
8. Duchesne, L.; Karangelos, E.; Wehenkel, L. Recent Developments in Machine Learning for Energy Systems Reliability Management. *Proc. IEEE* **2020**, *108*, 1656–1676. [CrossRef]
9. Joshi, A.; Capezza, S.; Alhaji, A.; Chow, M.-Y. Survey on AI and Machine Learning Techniques for Microgrid Energy Management Systems. *IEEE/CAA J. Autom. Sin.* **2023**, *10*, 1513–1529. [CrossRef]
10. Elsisi, M.; Amer, M.; Dababat, A.; Su, C.-L. A comprehensive review of machine learning and IoT solutions for demand side energy management, conservation, and resilient operation. *Energy* **2023**, *281*, 128256. [CrossRef]
11. Azevedo, B.F.; Rocha, A.M.A.C.; Pereira, A.I. Hybrid approaches to optimization and machine learning methods: A systematic literature review. *Mach. Learn.* **2024**, *113*, 4055–4097. [CrossRef]
12. Bin Abu Sofian, A.D.; Lim, H.R.; Siti Halimatul Munawaroh, H.; Ma, Z.; Chew, K.W.; Show, P.L. Machine learning and the renewable energy revolution: Exploring solar and wind energy solutions for a sustainable future including innovations in energy storage. In *Sustainable Development*; Wiley: Hoboken, NJ, USA, 2024.
13. Thakkar, P.; Khatri, S.; Dobariya, D.; Patel, D.; Dey, B.; Singh, A.K. Advances in materials and machine learning techniques for energy storage devices: A comprehensive review. *J. Energy Storage* **2024**, *81*, 110452. [CrossRef]
14. Kurucan, M.; Özbaltan, M.; Yetgin, Z.; Alkaya, A. Applications of artificial neural network based battery management systems: A literature review. *Renew. Sustain. Energy Rev.* **2024**, *192*, 114262. [CrossRef]
15. Latrach, A.; Malki, M.L.; Morales, M.; Mehana, M.; Rabiei, M. A critical review of physics-informed machine learning applications in subsurface energy systems. *Geoenergy Sci. Eng.* **2024**, *239*, 212938. [CrossRef]
16. Eren, Y.; Küçükdemiral, I. A comprehensive review on deep learning approaches for short-term load forecasting. *Renew. Sustain. Energy Rev.* **2024**, *18*, 114031. [CrossRef]
17. Luo, X.; Mahdjoubi, L. Towards a blockchain and machine learning-based framework for decentralised energy management. *Energy Build.* **2024**, *303*, 113757. [CrossRef]

18. Zhou, Y.; Zheng, S.; Hensen, J.L. Machine learning-based digital district heating/cooling with renewable integrations and advanced low-carbon transition. *Renew. Sustain. Energy Rev.* **2024**, *199*, 114466. [CrossRef]
19. Khan, M.R.; Haider, Z.M.; Malik, F.H.; Almasoudi, F.M.; Alatawi, K.S.S.; Bhutta, M.S. A Comprehensive Review of Microgrid Energy Management Strategies Considering Electric Vehicles, Energy Storage Systems, and AI Techniques. *Processes* **2024**, *12*, 270. [CrossRef]
20. Song, D.; Shen, G.; Huang, C.; Huang, Q.; Yang, J.; Dong, M.; Joo, Y.H.; Duić, N. Review on the Application of Artificial Intelligence Methods in the Control and Design of Offshore Wind Power Systems. *J. Mar. Sci. Eng.* **2024**, *12*, 424. [CrossRef]
21. Arafat, M.; Hossain, M.; Alam, M. Machine learning scopes on microgrid predictive maintenance: Potential frameworks, challenges, and prospects. *Renew. Sustain. Energy Rev.* **2024**, *190*, 114088. [CrossRef]
22. Wang, X.; Wang, H.; Bhandari, B.; Cheng, L. AI-empowered methods for smart energy consumption: A review of load forecasting, anomaly detection and demand response. *Int. J. Precis. Eng. Manuf.-Green Technol.* **2024**, *11*, 963–993. [CrossRef]
23. Al-Ismail, F.S. A Critical Review on DC Microgrids Voltage Control and Power Management. *IEEE Access* **2024**, *12*, 30345–30361. [CrossRef]
24. Jathar, L.D.; Nikam, K.; Awasarmol, U.V.; Gurav, R.; Patil, J.D.; Shahapurkar, K.; Soudagar, M.E.M.; Khan, T.M.Y.; Kalam, M.; Hnydiuk-Stefan, A.; et al. A comprehensive analysis of the emerging modern trends in research on photovoltaic systems and desalination in the era of artificial intelligence and machine learning. *Heliyon* **2024**, *10*, e25407. [CrossRef] [PubMed]
25. Ruan, G.; Qiu, D.; Sivaranjani, S.; Awad, A.S.; Strbac, G. Data-driven energy management of virtual power plants: A review. *Adv. Appl. Energy* **2024**, *14*, 100170. [CrossRef]
26. SaberiKamarposhti, M.; Kamyab, H.; Krishnan, S.; Yusuf, M.; Rezania, S.; Chelliapan, S.; Khorami, M. A comprehensive review of AI-enhanced smart grid integration for hydrogen energy: Advances, challenges, and future prospects. *Int. J. Hydrogen Energy* **2024**, *67*, 1009–1025. [CrossRef]
27. Zheng, Z.; Shafique, M.; Luo, X.; Wang, S. A systematic review towards integrative energy management of smart grids and urban energy systems. *Renew. Sustain. Energy Rev.* **2024**, *189*, 114023. [CrossRef]
28. Kishore, P.S.V.; Rajesh, J.; Jayaram, N.; Halder, S. A Survey of Machine Learning Applications in Renewable Energy Sources. *IETE J. Res.* **2024**, *70*, 1389–1406. [CrossRef]
29. Shoaei, M.; Noorollahi, Y.; Hajinezhad, A.; Moosavian, S.F. A review of the applications of artificial intelligence in renewable energy systems: An approach-based study. *Energy Convers. Manag.* **2024**, *306*, 118207. [CrossRef]
30. Zia, M.F.; Elbouchikhi, E.; Benbouzid, M. Microgrids energy management systems: A critical review on methods, solutions, and prospects. *Appl. Energy* **2018**, *222*, 1033–1055. [CrossRef]
31. Moghimi, S.M.; Gulliver, T.A.; Chelvan, I.T. Energy Management in Modern Buildings Based on Demand Prediction and Machine Learning—A Review. *Energies* **2024**, *17*, 555. [CrossRef]
32. Bibri, S.E.; Krogstie, J.; Kaboli, A.; Alahi, A. Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review. *Environ. Sci. Ecotechnology* **2024**, *19*, 100330. [CrossRef] [PubMed]
33. Shahcheraghian, A.; Madani, H.; Ilinca, A. From White to Black-Box Models: A Review of Simulation Tools for Building Energy Management and Their Application in Consulting Practices. *Energies* **2024**, *17*, 376. [CrossRef]
34. Ardabili, S.; Abdolalizadeh, L.; Mako, C.; Torok, B.; Mosavi, A. Systematic Review of Deep Learning and Machine Learning for Building Energy. *Front. Energy Res.* **2022**, *10*, 786027. [CrossRef]
35. Chen, Z.; Xiao, F.; Guo, F.; Yan, J. Interpretable machine learning for building energy management: A state-of-the-art review. *Adv. Appl. Energy* **2023**, *9*, 100123. [CrossRef]
36. Raza, A.; Jingzhao, L.; Ghadi, Y.; Adnan, M.; Ali, M. Smart home energy management systems: Research challenges and survey. *Alex. Eng. J.* **2024**, *92*, 117–170. [CrossRef]
37. Lissa, P.; Deane, C.; Schukat, M.; Seri, F.; Keane, M.; Barrett, E. Deep reinforcement learning for home energy management system control. *Energy AI* **2021**, *3*, 100043. [CrossRef]
38. Yussuf, R.O.; Asfour, O.S. Applications of artificial intelligence for energy efficiency throughout the building lifecycle: An overview. *Energy Build.* **2024**, *305*, 113903. [CrossRef]
39. Mason, K.; Grijalva, S. A review of reinforcement learning for autonomous building energy management. *Comput. Electr. Eng.* **2019**, *78*, 300–312. [CrossRef]
40. Alalwany, E.; Mahgoub, I. Security and Trust Management in the Internet of Vehicles (IoV): Challenges and Machine Learning Solutions. *Sensors* **2024**, *24*, 368. [CrossRef] [PubMed]
41. Azim Mohseni, N.; Bayati, N.; Ebel, T. Energy management strategies of hybrid electric vehicles: A comparative review. *IET Smart Grid* **2024**, *7*, 191–220. [CrossRef]
42. Fayyazi, M.; Sardar, P.; Thomas, S.I.; Daghigh, R.; Jamali, A.; Esch, T.; Kemper, H.; Langari, R.; Khayyam, H. Artificial intelligence/machine learning in energy management systems, control, and optimization of hydrogen fuel cell vehicles. *Sustainability* **2023**, *15*, 5249. [CrossRef]
43. Oladosu, T.L.; Pasupuleti, J.; Kiong, T.S.; Koh, S.P.; Yusaf, T. Energy management strategies, control systems, and artificial intelli-gence-based algorithms development for hydrogen fuel cell-powered vehicles: A review. *Int. J. Hydrogen Energy* **2024**, *61*, 1380–1404. [CrossRef]

44. He, H.; Meng, X.; Wang, Y.; Khajepour, A.; An, X.; Wang, R.; Sun, F. Deep reinforcement learning based energy management strategies for electrified vehicles: Recent advances and perspectives. *Renew. Sustain. Energy Rev.* **2024**, *192*, 114248. [CrossRef]
45. Lee, H.; Song, C.; Kim, N.; Cha, S.W. Comparative Analysis of Energy Management Strategies for HEV: Dynamic Programming and Reinforcement Learning. *IEEE Access* **2020**, *8*, 67112–67123. [CrossRef]
46. Choi, I.-H.; Lee, J.-H.; Hong, S.-H. Implementation and evaluation of the apparatus for intelligent energy management to apply to the smart grid at home. In Proceedings of the 2011 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Hangzhou, China, 10–12 May 2011; pp. 1–5.
47. STAFF REPORT. Demand Response & Advanced Metering. FERC. 2006. Available online: https://www.ferc.gov/legal/staff-reports/demand-response.pdf (accessed on 11 November 2024).
48. Peng, L.; Yan, G.-S. Clean Energy Grid-Connected Technology Based on Smart Grid. *Energy Procedia* **2011**, *12*, 213–218. [CrossRef]
49. Hou, H.; Zhou, J.; Zhang, Y.; He, X. A Brief Analysis on Differences of Risk Assessment Between Smart Grid and Traditional Power Grid. In Proceedings of the 2011 Fourth International Symposium on Knowledge Acquisition and Modeling (KAM), Sanya, China, 8–9 October 2011; pp. 188–191.
50. Alvial-Palavicino, C.; Garrido-Echeverria, N.; Jimenez-Estevez, G.; Reyes, L.; PalmaBehnke, R. A methodology for community en-gagement in the introduction of renewable based smart micro grid. *Energy Sustain. Dev.* **2011**, *15*, 314–323. [CrossRef]
51. Agrell, P.J.; Bogetoft, P.; Mikkers, M. Smart-grid investments, regulation and organization. *Energy Policy* **2013**, *52*, 656–666. [CrossRef]
52. Moretti, M.; Djomo, S.N.; Azadi, H.; May, K.; De Vos, K.; Van Passel, S.; Witters, N. A systematic review of environmental and economic impacts of smart grids. *Renew. Sustain. Energy Rev.* **2017**, *68*, 888–898. [CrossRef]
53. Cunjiang, Y.; Huaxun, Z.; Lei, Z. Architecture Design for Smart Grid. *Energy Procedia* **2012**, *17*, 1524–1528. [CrossRef]
54. Tuballa, M.L.; Abundo, M.L. A review of the development of smart grid technologies. *Renew. Sustain. Energy Rev.* **2016**, *59*, 710–725. [CrossRef]
55. Lin, S.-Y.; Chen, J.-F. Distributed optimal power flow for smart grid transmission system with renewable energy sources. *Energy* **2013**, *56*, 184–192. [CrossRef]
56. Gungor, V.C.; Sahin, D.; Kocak, T.; Ergut, S.; Buccella, C.; Cecati, C.; Hancke, G.P. Smart Grid Technologies: Communication Technologies and Standards. *IEEE Trans. Ind. Inform.* **2011**, *7*, 529–539. [CrossRef]
57. Gao, J.; Xiao, Y.; Liu, J.; Liang, W.; Chen, C.P. A survey of communication/networking in Smart Grids. *Futur. Gener. Comput. Syst.* **2012**, *28*, 391–404. [CrossRef]
58. Alonso, M.; Amaris, H.; Alvarez-Ortega, C. Integration of renewable energy sources in smart grids by means of evolutionary optimization algorithms. *Expert Syst. Appl.* **2012**, *39*, 5513–5522. [CrossRef]
59. Markovic, D.S.; Zivkovic, D.; Branovic, I.; Popovic, R.; Cvetkovic, D. Smart power grid and cloud computing. *Renew. Sustain Energy Rev.* **2013**, *24*, 566–577. [CrossRef]
60. Colak, I.; Sagiroglu, S.; Fulli, G.; Yesilbudak, M.; Covrig, C.F. A survey on the critical issues in smart grid technologies. *Renew. Sustain. Energy Rev.* **2016**, *54*, 396–405. [CrossRef]
61. Kakran, S.; Chanana, S. Smart operations of smart grids integrated with distributed generation: A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 524–535. [CrossRef]
62. Sun, D.Q.; Zheng, J.W.; Zhang, T.; Zhang, Z.J.; Liu, H.T.; Zhao, F.; Qiu, Z.J. The Utilization and Development Strategies of Smart Grid and New Energy. In Proceedings of the 2010 Asia-Pacific Power and Energy Engineering Conference, Chengdu, China, 28–31 March 2010; pp. 1–4.
63. Masters, G.M. *Renewable and Efficient Electric Power Systems*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2004.
64. Maharjan, S.; Zhang, Y.; Gjessing, S.; Tsang, D. User-centric demand response management in the smart grid with multiple pro-viders. *IEEE Trans. Emerg. Top. Comput.* **2014**, *5*, 494–505. [CrossRef]
65. Howlader, H.O.R.; Matayoshi, H.; Senjyu, T. Distributed generation incorporated with the thermal generation for optimum operation of a smart grid considering forecast error. *Energy Convers. Manag.* **2015**, *96*, 303–314. [CrossRef]
66. Sun, S.; Dong, M.; Liang, B. Distributed Real-Time Power Balancing in Renewable-Integrated Power Grids with Storage and Flexible Loads. *IEEE Trans. Smart Grid* **2016**, *7*, 2337–2349. [CrossRef]
67. Chen, C.-L. Optimal Wind–Thermal Generating Unit Commitment. *IEEE Trans. Energy Convers.* **2008**, *23*, 273–280. [CrossRef]
68. Chen, C.-L. Simulated annealing-based optimal wind-thermal coordination scheduling. *IET Gener. Transm. Distrib.* **2007**, *1*, 447–455. [CrossRef]
69. Ummels, B.C.; Gibescu, M.; Pelgrum, E.; Kling, W.L.; Brand, A.J. Impacts of Wind Power on Thermal Generation Unit Commitment and Dispatch. *IEEE Trans. Energy Convers.* **2007**, *22*, 44–51. [CrossRef]
70. Ilic, M.D.; Xie, L.; Joo, J.-Y. Efficient Coordination of Wind Power and Price-Responsive Demand—Part I: Theoretical Foundations. *IEEE Trans. Power Syst.* **2011**, *26*, 1875–1884. [CrossRef]
71. Batista, N.C.; Melicio, R.; Matias, J.C.O.; Catalao, J.P.S. Photo voltaic and wind energy systems monitoring and building/home energy management using ZigBee devices within a smartgrid. *Energy* **2013**, *49*, 306–315. [CrossRef]
72. Faria, P.; Soares, J.; Vale, Z.; Morais, H.; Sousa, T. Modified particle swarm optimization applied to integrated demand response and DG resources scheduling. *IEEE Trans. Smart Grid* **2013**, *4*, 606–616. [CrossRef]
73. Wu, H.; Shahidehpour, M.; Al-Abdulwahab, A. Hourly demand response in day-ahead scheduling for managing the variability of renewable energy. *IET Gener. Transm. Distrib.* **2013**, *7*, 226–234. [CrossRef]

74. Paterakis, N.G.; Medeiros, M.F.; Catalao, J.P.S.; Erdinc, O. Distribution system operation enhancement through household consump-tion coordination in a dynamic pricing environment. In Proceedings of the 2015 IEEE Eindhoven PowerTech, Eindhoven, The Netherlands, 29 June–2 July 2015; pp. 1–6.
75. Werth, A.; Kitamura, N.; Tanaka, K. Conceptual Study for Open Energy Systems: Distributed Energy Network Using Interconnected DC Nanogrids. *IEEE Trans. Smart Grid* **2015**, *6*, 1621–1630. [CrossRef]
76. Jiang, Z.; Dougal, R.A. Hierarchical microgrid paradigm for integration of distributed energy resources. In Proceedings of the 2008 IEEE Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, USA, 20–24 July 2008; pp. 1–8.
77. Carrasco, J.M.; Franquelo, L.G.; Bialasiewicz, J.T.; Galván, E.; PortilloGuisado, R.C.; Prats, M.M. Power-electronic systems for the grid integration of renewable energy sources: A survey. *IEEE Trans. Ind. Electron.* **2006**, *53*, 1002–1016. [CrossRef]
78. Tushar, M.H.K.; Assi, C.; Maier, M.; Uddin, M.F. Smart Microgrids: Optimal Joint Scheduling for Electric Vehicles and Home Appliances. *IEEE Trans. Smart Grid* **2014**, *5*, 239–250. [CrossRef]
79. Atwa, Y.M.; El-Saadany, E.F.; Salama, M.M.A.; Seethapathy, R. Optimal Renewable Resources Mix for Distribution System Energy Loss Minimization. *IEEE Trans. Power Syst.* **2010**, *25*, 360–370. [CrossRef]
80. He, M.; Murugesan, S.; Zhang, J. A Multi-timescale scheduling approach for stochastic reliability in smart grids with wind gen-eration and opportunistic demand. *IEEE Trans. Smart Grid* **2013**, *4*, 521–529. [CrossRef]
81. Joel, K.; Phil, C.; Ashish, A. A review of protection systems for distribution networks embedded with re-newable generation. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1308–1317.
82. Tendayi, M.P.; Ramesh, B. Renewable distributed generation: The hidden challenges—A review from the protection perspective. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1457–1465.
83. Shashank, V.; Rajesh, K.; Rajesh, K. Data analytics and computational methods for anti-islanding of renewable energy based Distributed Generators in power grids. *Renew. Sustain. Energy Rev.* **2017**, *69*, 493–502.
84. Rosales-Asensio, E.; Diez, D.B.; Sarmento, P. Electricity balancing challenges for markets with high variable renewable generation. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113918. [CrossRef]
85. Eftekharnejad, S.; Vittal, V.; Heydt, G.T.; Keel, B.; Loehr, J.; Heydt, G.T. Impact of increased penetration of photovoltaic generation on power systems. *IEEE Trans. Power Syst.* **2013**, *28*, 893–901. [CrossRef]
86. Adika, C.O.; Wang, L. Autonomous appliance scheduling for household energy management. *IEEE Trans Smart Grid* **2014**, *5*, 673–682. [CrossRef]
87. Chaouachi, A.; Kamel, R.M.; Andoulsi, R.; Nagasaka, K. Multiobjective Intelligent Energy Management for a Microgrid. *IEEE Trans. Ind. Electron.* **2013**, *60*, 1688–1699. [CrossRef]
88. Hetzer, J.; Yu, D.C.; Bhattarai, K. An Economic Dispatch Model Incorporating Wind Power. *IEEE Trans. Energy Convers.* **2008**, *23*, 603–611. [CrossRef]
89. Arulampalam, A.; Barnes, M.; Jenkins, N.; Ekanayake, J. Power quality and stability improvement of a wind farm using STATCOM supported with hybrid battery energy storage. *IEE Proc.-Gener. Transm. Distrib.* **2006**, *153*, 701–710. [CrossRef]
90. Muljadi, E.; Butterfield, C.; Yinger, R.; Romanowitz, H. Energy Storage and Reactive Power Compensator in a Large Wind Farm. In Proceedings of the 42nd AIAA Aerospace Sciences Meeting and Exhibit, Reno, NV, USA, 5–8 January 2004.
91. Diaz, N.L.; Dragicevic, T.; Vasquez, J.C.; Guerrero, J.M. Intelligent Distributed Generation and Storage Units for DC Microgrids—A New Concept on Cooperative Control Without Communications Beyond Droop Control. *IEEE Trans. Smart Grid* **2014**, *5*, 2476–2485. [CrossRef]
92. Teleke, S.; Baran, M.E.; Bhattacharya, S.; Huang, A.Q. Rule-Based Control of Battery Energy Storage for Dispatching Intermittent Renewable Sources. *IEEE Trans. Sustain. Energy* **2010**, *1*, 117–124. [CrossRef]
93. Erdinc, O.; Paterakis, N.G.; Mendes, T.D.P.; Bakirtzis, A.G.; Catalao, J.P.S. Smart Household Operation Considering Bi-Directional EV and ESS Utilization by Real-Time Pricing-Based DR. *IEEE Trans. Smart Grid* **2015**, *6*, 1281–1291. [CrossRef]
94. Wang, Y.; Sheikh, O.; Hu, B.; Chu, C.C.; Gadh, R. Integration of V2H/V2G hybrid system for demand response in distribution network. In Proceedings of the 2014 IEEE International Conference on Smart Grid Communications (Smart Grid Comm.), Venice, Italy, 3–6 November 2014; pp. 812–817.
95. Wang, Z.; Gu, C.; Li, F.; Bale, P.; Sun, H. Active Demand Response Using Shared Energy Storage for Household Energy Management. *IEEE Trans. Smart Grid* **2013**, *4*, 1888–1897. [CrossRef]
96. Wang, L.; Collins, E.G.; Li, H. Optimal Design and Real-Time Control for Energy Management in Electric Vehicles. *IEEE Trans. Veh. Technol.* **2011**, *60*, 1419–1429. [CrossRef]
97. Le, H.T.; Santoso, S.; Grady, W.M. Development and analysis of an ESS-based application for regulating wind farm power output variation. In Proceedings of the 2009 IEEE Power Energy Society General Meeting (PES), Calgary, AB, Canada, 26–30 July 2009; pp. 1–8.
98. Vodovozov, V.; Raud, Z.; Petlenkov, E. Review on Braking Energy Management in Electric Vehicles. *Energies* **2021**, *14*, 4477. [CrossRef]
99. Sabri, M.; Danapalasingam, K.A.; Rahmat, M.F. A review on hybrid electric vehicles architecture and energy management strate-gies. *Renew. Sustain. Energy Rev.* **2016**, *53*, 1433–1442. [CrossRef]
100. Safari, A.; Sorouri, H.; Oshnoei, A.; Blaabjerg, F. A Brain Emotional Learning-Based Speed Control Strategy for DC Motors. In Proceedings of the IEEE 15th International Symposium on Power Electronics for Distributed Generation Systems (PEDG 2024), Luxembourg, 23–26 June 2024.

101. Safari, A.; Sorouri, H.; Oshnoei, A. The Regulation of Superconducting Magnetic Energy Storages with a Neural-Tuned Fractional Order PID Controller Based on Brain Emotional Learning. *Fractal Fract.* **2024**, *8*, 365. [CrossRef]
102. Sam, K.-K.; Abd, R.N. Coordinated control of smart microgrid during and after islanding operation to prevent under frequency load shedding using energy storage system. *Energy Convers. Manag.* **2016**, *127*, 623–646.
103. Jia, C.; He, H.; Zhou, J.; Li, J.; Wei, Z.; Li, K. Learning-based model predictive energy management for fuel cell hybrid electric bus with health-aware control. *Appl. Energy* **2024**, *355*, 122228. [CrossRef]
104. Jia, C.; Zhou, J.; He, H.; Li, J.; Wei, Z.; Li, K. Health-conscious deep reinforcement learning energy management for fuel cell buses integrating environmental and look-ahead road information. *Energy* **2024**, *290*, 130146. [CrossRef]
105. Sadeghian, O.; Shotorbani, A.M.; Ghassemzadeh, S.; Mohammadi-Ivatloo, B. Energy management of hybrid fuel cell and renewable energy based systems—A review. *Int. J. Hydrogen Energy* **2024**. [CrossRef]
106. Li, K.; Zhou, J.; Jia, C.; Yi, F.; Zhang, C. Energy sources durability energy management for fuel cell hybrid electric bus based on deep reinforcement learning considering future terrain information. *Int. J. Hydrogen Energy* **2024**, *52*, 821–833. [CrossRef]
107. Liu, B.; Wei, X.; Sun, C.; Wang, B.; Huo, W. A controllable neural network-based method for optimal energy management of fuel cell hybrid electric vehicles. *Int. J. Hydrogen Energy* **2024**, *55*, 1371–1382. [CrossRef]
108. Safari, A.; Hayati, M.M.; Nazari-Heris, M. Hydrogen-Combined Smart Electrical Power Systems: An Overview of United States Projects. In *Green Hydrogen in Power Systems*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 321–340.
109. Hayati, M.M.; Safari, A.; Nazari-Heris, M.; Oshnoei, A. Hydrogen-Incorporated Sector-Coupled Smart Grids: A Systematic Review and Future Concepts. In *Green Hydrogen in Power Systems*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 25–58.
110. Panchenko, V.; Daus, Y.; Kovalev, A.; Yudaev, I.; Litti, Y. Prospects for the production of green hydrogen: Review of countries with high potential. *Int. J. Hydrogen Energy* **2023**, *48*, 4551–4571. [CrossRef]
111. Zhou, Y.; Li, R.; Lv, Z.; Liu, J.; Zhou, H.; Xu, C. Green hydrogen: A promising way to the carbon-free society. *Chin. J. Chem. Eng.* **2022**, *43*, 2–13. [CrossRef]
112. Hassan, Q.; Abdulateef, A.M.; Hafedh, S.A.; Al-Samari, A.; Abdulateef, J.; Sameen, A.Z.; Salman, H.M.; Al-Jiboory, A.K.; Wieteska, S.; Jaszczur, M. Renewable energy-to-green hydrogen: A review of main resources routes, processes and evaluation. *Int. J. Hydrogen Energy* **2023**, *48*, 17383–17408. [CrossRef]
113. Oliveira, A.M.; Beswick, R.R.; Yan, Y. A green hydrogen economy for a renewable energy society. *Curr. Opin. Chem. Eng.* **2021**, *33*, 100701. [CrossRef]
114. Abad, A.V.; Dodds, P.E. Green hydrogen characterisation initiatives: Definitions, standards, guarantees of origin, and challenges. *Energy Policy* **2020**, *138*, 111300. [CrossRef]
115. Atilhan, S.; Park, S.; El-Halwagi, M.M.; Atilhan, M.; Moore, M.; Nielsen, R.B. Green hydrogen as an alternative fuel for the shipping industry. *Curr. Opin. Chem. Eng.* **2021**, *31*, 100668. [CrossRef]
116. Noussan, M. Performance based approach for electricity generation in smart grids. *Appl. Energy* **2018**, *220*, 231–241. [CrossRef]
117. Bartłomiejczyk, M. Potential application of solar energy systems for electrified urban transportation systems. *Energies* **2018**, *11*, 954. [CrossRef]
118. Connolly, D.; Mathiesen, B.; Ridjan, I. A comparison between renewable transport fuels that can supplement or replace biofuels in a 100% renewable energy system. *Energy* **2014**, *73*, 110–125. [CrossRef]
119. Calvillo, C.F.; Sánchez-Miralles, A.; Villar, J. Energy management and planning in smart cities. *Renew. Sustain. Energy Rev.* **2016**, *55*, 273–287. [CrossRef]
120. Chai, D.S.; Wen, J.Z.; Nathwani, J. Simulation of cogeneration within the concept of smart energy networks. *Energy Convers. Manag.* **2013**, *75*, 453–465. [CrossRef]
121. Chen, Z.; Xiong, S.; Chen, Q.; Zhang, Y.; Yu, J.; Jiang, J.; Wu, C. Eco-driving: A scientometric and bibliometric analysis. *IEEE Trans. Intell. Transp. Syst.* **2022**, *12*, 22716–22736. [CrossRef]
122. Khalil, M.I.; Jhanjhi, N.Z.; Humayun, M.; Sivanesan, S.K.; Masud, M.; Hossain, M.S. Hybrid smart grid with sustainable energy efficient resources for smart cities. *Sustain Energy Technol Assess.* **2021**, *46*, 101211. [CrossRef]
123. Ozturk, M.; Dincer, I. A comprehensive review on power-to-gas with hydrogen options for cleaner applications. *Int. J. Hydrogen Energy* **2021**, *46*, 31511–31522. [CrossRef]
124. Al-Ismail, F.S. A Comprehensive and Critical Review on Integrated Electric Power and Gas Networks. *IEEE Access* **2024**, *2*, 143042–143057. [CrossRef]
125. Bevrani, H.; Golpîra, H.; Messina, A.R.; Hatziargyriou, N.; Milano, F.; Ise, T. Power system frequency control: An updated review of current solutions and new challenges. *Electr. Power Syst. Res.* **2021**, *194*, 107114. [CrossRef]
126. Fischer, J.; Guy, S. Reinterpreting regulations: Architects as intermediaries for zero carbon buildings. In *Shaping Urban Infrastructures*; Routledge: London, UK, 2012; pp. 160–174.
127. Kim, H.; Choi, H.; Kang, H.; An, J.; Yeom, S.; Hong, T. A systematic review of the smart energy conservation system: From smart homes to sustainable smart cities. *Renew. Sustain. Energy Rev.* **2021**, *140*, 110755. [CrossRef]
128. Hussain, M.M.; Akram, R.; Memon, Z.A.; Nazir, M.H.; Javed, W.; Siddique, M. Demand Side Management Techniques for Home Energy Management Systems for Smart Cities. *Sustainability* **2021**, *13*, 11740. [CrossRef]
129. Banjac, A.; Novak, H.; Vašak, M. Implementation of model predictive indoor climate control for hierarchical building energy management. *Control. Eng. Pract.* **2023**, *136*, 105536. [CrossRef]

130. Nolting, L.; Kies, A.; Schönegge, M.; Robinius, M.; Praktiknjo, A. Locating experts and carving out the state of the art: A systematic review on Industry 4.0 and energy system analysis. *Int. J. Energy Res.* **2019**, *43*, 3981–4002. [CrossRef]
131. Alkhalidi, A.; Qoaider, L.; Khashman, A.; Al-Alami, A.R.; Jiryes, S. Energy and water as indicators for sustainable city site selection and design in Jordan using smart grid. *Sustain. Cities Soc.* **2018**, *37*, 125–132. [CrossRef]
132. Moazeni, F.; Khazaei, J. Co-optimization of wastewater treatment plants interconnected with smart grids. *Appl. Energy* **2021**, *298*, 117150. [CrossRef]
133. Yigit, K.; Acarkan, B. A new electrical energy management approach for ships using mixed energy sources to ensure sustainable port cities. *Sustain. Cities Soc.* **2018**, *40*, 126–135. [CrossRef]
134. Burchart-Korol, D.; Jursova, S.; Folęga, P.; Korol, J.; Pustejovska, P.; Blaut, A. Environmental life cycle assessment of electric vehicles in Poland and the Czech Republic. *J. Clean. Prod.* **2018**, *202*, 476–487. [CrossRef]
135. Magliocchetti, D.; Gielow, M.; De Vigili, F.; Conti, G.; De Amicis, R. A Personal Mobility Assistant based on Ambient Intelligence to Promote Sustainable Travel Choices. *Procedia Comput. Sci.* **2011**, *5*, 892–899. [CrossRef]
136. Li, S.; Xie, F.; Huang, Y.; Lin, Z.; Liu, C. Optimizing workplace charging facility deployment and smart charging strategies. *Transp. Res. Part D Transp. Environ.* **2020**, *87*, 102481. [CrossRef]
137. Fragiacomo, P.; Piraino, F. Vehicle-to-grid application with hydrogen-based tram. *Energy Convers. Manag.* **2021**, *250*, 114915. [CrossRef]
138. Mehrjerdi, H.; Hemmati, R. Coordination of vehicle-to-home and renewable capacity resources for energy management in resil-ience and self-healing building. *Renew. Energy* **2020**, *146*, 568–579. [CrossRef]
139. Lund, P.D.; Mikkola, J.; Ypyä, J. Smart energy system design for large clean power schemes in urban areas. *J. Clean. Prod.* **2015**, *103*, 437–445. [CrossRef]
140. Bartłomiejczyk, M.; Jarzebowicz, L.; Kohout, J. Compensation of Voltage Drops in Trolleybus Supply System Using Battery-Based Buffer Station. *Energies* **2022**, *15*, 1629. [CrossRef]
141. Del Granado, P.C.; Pang, Z.; Wallace, S.W. Synergy of smart grids and hybrid distributed generation on the value of energy storage. *Appl. Energy* **2016**, *170*, 476–488. [CrossRef]
142. Brunelli, L.; Borri, E.; Pisello, A.L.; Nicolini, A.; Mateu, C.; Cabeza, L.F. Thermal energy storage in energy communities: A perspective overview through a bibliometric analysis. *Sustainability* **2024**, *16*, 5895. [CrossRef]
143. Howell, S.; Rezgui, Y.; Hippolyte, J.L.; Jayan, B.; Li, H. Towards the next generation of smart grids: Semantic and holonic multi-agent management of distributed energy resources. *Renew. Sustain. Energy Rev.* **2017**, *77*, 193–214. [CrossRef]
144. Safari, A.; Ghavifekr, A.A. Use case of artificial intelligence and neural networks in energy consumption markets and industrial demand response. In *Industrial Demand Response: Methods, Best Practices, Case Studies, and Applications*; IET: London, UK, 2022; Volume 4, p. 379.
145. Khan, S.U.; Mehmood, K.K.; Haider, Z.M.; Bukhari, S.B.A.; Lee, S.-J.; Rafique, M.K.; Kim, C.-H. Energy Management Scheme for an EV Smart Charger V2G/G2V Application with an EV Power Allocation Technique and Voltage Regulation. *Appl. Sci.* **2018**, *8*, 648. [CrossRef]
146. Nasir, T.; Raza, S.; Abrar, M.; Muqeet, H.A.; Jamil, H.; Qayyum, F.; Cheikhrouhou, O.; Alassery, F.; Hamam, H. Optimal scheduling of campus microgrid considering the electric vehicle integration in smart grid. *Sensors* **2021**, *21*, 7133. [CrossRef]
147. Zolfaghari, M.; Ghaffarzadeh, N.; Ardakani, A.J. Optimal sizing of battery energy storage systems in off-grid micro grids using convex optimization. *J. Energy Storage* **2019**, *23*, 44–56. [CrossRef]
148. Ganesan, S.; Subramaniam, U.; Ghodke, A.A.; Elavarasan, R.M.; Raju, K.; Bhaskar, M.S. Investigation on Sizing of Voltage Source for a Battery Energy Storage System in Microgrid with Renewable Energy Sources. *IEEE Access* **2020**, *8*, 188861–188874. [CrossRef]
149. Shahab, H.A.M.M.; Wang, S.; ul Muqeet, H.A. Advanced Optimal Design of the IoT Based University Campus Microgrid Considering Environmental Concerns and Demand Response. In Proceedings of the 2021 6th International Conference on Power and Renewable Energy (ICPRE), Shanghai, China, 17–20 September 2021.
150. Mehmood, K.K.; Kim, C.-H.; Khan, S.U.; Haider, Z.M. Unified planning of wind generators and switched capacitor banks: A multiagent clustering-based distributed approach. *IEEE Trans. Power Syst.* **2018**, *33*, 6978–6988. [CrossRef]
151. Zaman, M.S.U.; Bukhari, S.B.A.; Hazazi, K.M.; Haider, Z.M.; Haider, R.; Kim, C.-H. Frequency response analysis of a single-area power system with a modified LFC model considering demand response and virtual inertia. *Energies* **2018**, *11*, 787. [CrossRef]
152. Wang, M.; Zhang, X.; Zhao, T.; Zhuang, F.; Wanga, F.; Qian, N.; Yang, S. Module Power Balance Control Strategy for Three-Phase Cascaded H-Bridge PV Inverter Under Unbalanced Grid Voltage Condition. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *9*, 5657–5671. [CrossRef]
153. Prince, S.K.; Panda, K.P.; Kumar, V.N.; Panda, G. Power quality enhancement in a distribution network using PSO assisted Kalman filter—Based shunt active power filter. In Proceedings of the 2018 IEEMA Engineer Infinite Conference (eTechNxT), New Delhi, India, 13–14 March 2018; pp. 1–6.
154. Bhargavi, K.M.; Jayalaksmi, N.S.; Malagi, S.; Jadoun, V.K. Integration of Plug-in Electric Vehicles in Smart Grid: A Review. In Proceedings of the 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC), Mathura, India, 28–29 February 2020; pp. 214–219.
155. Brenna, M.; Longo, M.; Yaïci, W. Modelling and Simulation of Electric Vehicle Fast Charging Stations Driven by High Speed Railway Systems. *Energies* **2017**, *10*, 1268. [CrossRef]

156. Aydogmus, O.; Boztas, G.; Celikel, R. Design and analysis of a flywheel energy storage system fed by matrix converter as a dynamic voltage restorer. *Energy* **2022**, *238*, 121687. [CrossRef]
157. Wang, Y.; Wang, C.; Xue, H. A novel capacity configuration method of flywheel energy storage system in electric vehicles fast charging station. *Electr. Power Syst. Res.* **2021**, *195*, 107185. [CrossRef]
158. Castro, G.A.; Murkowska, M.I.; Rey, P.Z.; Anvari-Moghaddam, A. Operational Planning of a Hybrid Power Plant for Off-Grid Mining Site: A Risk-constrained Optimization Approach. In Proceedings of the IECON 2020—46th Annual Conference of the IEEE Industrial Electronics Society, Singapore, 18–21 October 2020; pp. 4587–4592.
159. Abdali, A.; Mazlumi, K.; Rabiee, A. Harmonics impact on hotspot temperature increment of distribution transformers: Nonuniform magnetic-thermal approach. *Int. J. Electr. Power Energy Syst.* **2024**, *157*, 109826. [CrossRef]
160. Khaloie, H.; Anvari-Moghaddam, A. Robust Optimization Approach for Generation Scheduling of a Hybrid Thermal-Energy Storage System. *IEEE Int. Symp. Ind. Electron.* **2020**, *2020*, 971–976.
161. Wang, J.; Zheng, T.; Cheng, S. Coordination Control of Battery Energy Storage and MTGS in An Independent AC Micro-grid. In Proceedings of the 2019 IEEE 8th International Conference on Advanced Power System Automation and Protection (APAP), Xi'an, China, 21–24 October 2019; pp. 1657–1661.
162. Marinakis, V.; Doukas, H.; Tsapelas, J.; Mouzakitis, S.; Sicilia, Á.; Madrazo, L.; Sgouridis, S. From big data to smart energy services: An application for intelligent energy management. *Futur. Gener. Comput. Syst.* **2020**, *110*, 572–586. [CrossRef]
163. Marinakis, V.; Doukas, H.; Xidonas, P.; Zopounidis, C. Multicriteria decision support in local energy planning: An evaluation of alternative scenarios for the Sustainable Energy Action Plan. *Omega* **2017**, *69*, 1–16. [CrossRef]
164. Marinakis, V.; Papadopoulou, A.G.; Doukas, H.; Psarras, J. A web tool for sustainable energy communities. *Int. J. Inf. Decis. Sci.* **2015**, *7*, 18. [CrossRef]
165. Zhou, K.; Fu, C.; Yang, S. Big data driven smart energy management: From big data to big insights. *Renew. Sustain. Energy Rev.* **2016**, *56*, 215–225. [CrossRef]
166. Angelopoulos, M.; Kontakou, C. Big Data Analytics for Energy Efficiency. *Arch. Bus. Res.* **2022**, *8*, 15–23. [CrossRef]
167. Parent, C.; Spaccapietra, S. Issues and approaches of database integration. *Commun. ACM* **1998**, *41*, 166–178. [CrossRef]
168. Devogele, T.; Parent, C.; Spaccapietra, S. On spatial database integration. *Int. J. Geogr. Inf. Sci.* **1998**, *12*, 335–352. [CrossRef]
169. Xie, J.; Alvarez-Fernandez, I.; Sun, W. A Review of Machine Learning Applications in Power System Resilience. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020; pp. 1–5.
170. Sadek, S.M.; Omran, W.A.; Hassan, M.M.; Talaat, H.E. Data Driven Stochastic Energy Management for Isolated Microgrids Based on Generative Adversarial Networks Considering Reactive Power Capabilities of Distributed Energy Resources and Reactive Power Costs. *IEEE Access* **2021**, *9*, 5397–5411. [CrossRef]
171. Shrouf, F.; Ordieres-Meré, J.; García-Sánchez, A.; Ortega-Mier, M. Optimizing the production scheduling of a single machine to minimize total energy consumption costs. *J. Clean. Prod.* **2014**, *67*, 197207. [CrossRef]
172. Kimm, G. Classes of AI tools, techniques, and methods. In *Artificial Intelligence in Urban Planning and Design*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 61–83.
173. Mellit, A.; Kalogirou, S.A. ANFIS-based modelling for photovoltaic power supply system: A case study. *Renew. Energy* **2011**, *36*, 250–258. [CrossRef]
174. McCulloch, W.S.; Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biol.* **1990**, *52*, 99–115. [CrossRef] [PubMed]
175. Jang, J.-S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
176. Hochreiter, S.; Schmidhuber, J. Long short-term memory. *Neural Comput.* **1997**, *9*, 1735–1780. [CrossRef] [PubMed]
177. Schuster, M.; Paliwal, K.K. Bidirectional recurrent neural networks. *IEEE Trans. Signal Process.* **1997**, *45*, 2673–2681. [CrossRef]
178. Quinlan, J.R. Induction of decision trees. *Mach. Learn.* **1986**, *1*, 81–106. [CrossRef]
179. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
180. Sutton, R.S.; Barto, A.G. *Reinforcement Learning: An Introduction*; MIT Press: Cambridge, MA, USA, 2017.
181. Wiering, M.A.; Otterlo, M.V. Reinforcement learning. *Adapt. Learn. Optim.* **2012**, *12*, 729.
182. Silvetti, M.; Verguts, T. Reinforcement learning, high-level cognition, and the human brain. In *Neuroimaging–Cognitive and Clinical Neuroscience*; Intech Open: Manhattan, NY, USA, 2012; pp. 283–296.
183. Gupta, P. *Introduction to Machine Learning in the Cloud with Python: Concepts and Practices*; Springer Nature: Berlin/Heidelberg, Germany, 2021.
184. Hatziargyriou, N.; Milanovic, J.; Rahmann, C.; Ajjarapu, V.; Canizares, C.; Erlich, I.; Hill, D.; Hiskens, I.; Kamwa, I.; Pal, B.; et al. Definition and Classification of Power System Stability—Revisited & Extended. *IEEE Trans. Power Syst.* **2020**, *36*, 3271–3281. [CrossRef]
185. Parvez, I.; Aghili, M.; Sarwat, A.I.; Rahman, S.; ALAM, F. Online power quality disturbance detection by support vector machine in smart meter. *J. Mod. Power Syst. Clean Energy* **2019**, *7*, 1328–1339. [CrossRef]
186. Impram, S.; Nese, S.V.; Oral, B. Challenges of renewable energy penetration on power system flexibility: A survey. *Energy Strat. Rev.* **2020**, *31*, 100539. [CrossRef]
187. Shi, Z.; Yao, W.; Li, Z.; Zeng, L.; Zhao, Y.; Zhang, R.; Tang, Y.; Wen, J. Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions. *Appl. Energy* **2020**, *278*, 115733. [CrossRef]

188. Shi, Z.; Yao, W.; Tang, Y.; Ai, X.; Wen, J.; Cheng, S. Bidirectional Active Transfer Learning for Adaptive Power System Stability Assessment and Dominant Instability Mode Identification. *IEEE Trans. Power Syst.* **2022**, *38*, 5128–5142. [CrossRef]
189. Safari, A.; Sabahi, M.; Oshnoei, A. ResFaultyMan: An intelligent fault detection predictive model in power electronics systems using unsupervised learning isolation forest. *Heliyon* **2024**, *10*, e35243. [CrossRef]
190. Xi, L.; Wu, J.; Xu, Y.; Sun, H. Automatic Generation Control Based on Multiple Neural Networks with Actor-Critic Strategy. *IEEE Trans. Neural Networks Learn. Syst.* **2020**, *32*, 2483–2493. [CrossRef]
191. Regad, M.; Helaimi, M.; Taleb, R.; Othman, A.M.; Gabbar, H.A. Control of hybrid power system based renewable energy generations using PID controller. *Int. J. Power Electron. Drive Syst.* **2020**, *11*, 1775–1784. [CrossRef]
192. Satyanarayana, S.; Sharma, R.K.; Sappa, A.K. Automatic Generation control in power plant using PID, PSS and fuzzy-PID controller. In Proceedings of the IEEE 2014 International Conference on Smart Electric Grid (ISEG), Guntur, India, 19–20 September 2014; pp. 1–8.
193. Hwang, M.; Muljadi, E.; Jang, G.; Kang, Y.C. Disturbance-Adaptive Short-Term Frequency Support of a DFIG Associated with the Variable Gain Based on the ROCOF and Rotor Speed. *IEEE Trans. Power Syst.* **2017**, *32*, 1873–1881. [CrossRef]
194. Kheshti, M.; Ding, L.; Bao, W.; Yin, M.; Wu, Q.; Terzija, V. Toward Intelligent Inertial Frequency Participation of Wind Farms for the Grid Frequency Control. *IEEE Trans. Ind. Inform.* **2020**, *16*, 6772–6786. [CrossRef]
195. Liang, Y.; Zhao, X.; Sun, L. A Multiagent Reinforcement Learning Approach for Wind Farm Frequency Control. *IEEE Trans. Ind. Inform.* **2023**, *19*, 1725–1734. [CrossRef]
196. Dong, H.; Zhao, X. Data-Driven Wind Farm Control via Multiplayer Deep Reinforcement Learning. *IEEE Trans. Control. Syst. Technol.* **2023**, *31*, 1468–1475. [CrossRef]
197. Yan, J.; Nuertayi, A.; Yan, Y.; Liu, S.; Liu, Y. Hybrid physical and data driven modeling for dynamic operation characteristic simulation of wind turbine. *Renew. Energy* **2023**, *215*, 118958. [CrossRef]
198. Monroc, C.B.; Bušić, A.; Dubuc, D.; Zhu, J. Actor critic agents for wind farm control. In Proceedings of the IEEE 2023 American Control Conference (ACC), San Diego, CA, USA, 31 May–2 June 2023; pp. 177–183.
199. Behara, R.K.; Saha, A.K. Artificial intelligence control system applied in smart grid integrated doubly fed induction generator-based wind turbine: A review. *Energies* **2022**, *17*, 6488. [CrossRef]
200. Cao, D.; Zhao, J.; Hu, W.; Ding, F.; Huang, Q.; Chen, Z. Attention Enabled Multi-Agent DRL for Decentralized Volt-VAR Control of Active Distribution System Using PV Inverters and SVCs. *IEEE Trans. Sustain. Energy* **2021**, *12*, 1582–1592. [CrossRef]
201. Khan, M.A.; Haque, A.; Kurukuru, V.S.B. Intelligent transition control approach for different operating modes of photo-voltaic inverter. *IEEE Trans. Ind.* **2022**, *58*, 2332–2340. [CrossRef]
202. Alam, M.J.E.; Muttaqi, K.M.; Sutanto, D. A Multi-Mode Control Strategy for VAr Support by Solar PV Inverters in Distribution Networks. *IEEE Trans. Power Syst.* **2015**, *30*, 1316–1326. [CrossRef]
203. Weckx, S.; Driesen, J. Optimal Local Reactive Power Control by PV Inverters. *IEEE Trans. Sustain. Energy* **2016**, *7*, 1624–1633. [CrossRef]
204. Fu, X.; Li, S.; Jaithwa, I. Implement Optimal Vector Control for LCL-Filter-Based Grid-Connected Converters by Using Recurrent Neural Networks. *IEEE Trans. Ind. Electron.* **2015**, *62*, 4443–4454. [CrossRef]
205. Hadidi, R.; Jeyasurya, B. Reinforcement learning based real-time wide-area stabilizing control agents to enhance power system stability. *IEEE Trans. Smart Grid* **2023**, *4*, 489–497. [CrossRef]
206. Hagmar, H.; Tong, L.; Eriksson, R. Voltage instability prediction using a deep recurrent neural network. *IEEE Trans. Power Syst.* **2022**, *36*, 17–27. [CrossRef]
207. Peng, F.Z. Flexible AC Transmission Systems (FACTS) and Resilient AC Distribution Systems (RACDS) in Smart Grid. *Proc. IEEE* **2017**, *105*, 2099–2115. [CrossRef]
208. Zheng, D.-D.; Madani, S.S.; Karimi, A. Data-Driven Distributed Online Learning Control for Islanded Microgrids. *IEEE J. Emerg. Sel. Top. Circuits Syst.* **2022**, *12*, 194–204. [CrossRef]
209. Zamzam, A.S.; Sidiropoulos, N.D. Physics-Aware Neural Networks for Distribution System State Estimation. *IEEE Trans. Power Syst.* **2020**, *35*, 4347–4356. [CrossRef]
210. Chen, Q.; Lin, N.; Bu, S.; Wang, H.; Zhang, B. Interpretable Time-Adaptive Transient Stability Assessment Based on Dual-Stage Attention Mechanism. *IEEE Trans. Power Syst.* **2023**, *38*, 2776–2790. [CrossRef]
211. Ye, X.; Yan, J.; Wang, Y.; Lu, L.; He, R. A Novel Capsule Convolutional Neural Network with Attention Mechanism for High-Voltage Circuit Breaker Fault Diagnosis. *Electr. Power Syst. Res.* **2022**, *209*, 108003. [CrossRef]
212. Wang, W.; Yu, N.; Gao, Y.; Shi, J. Safe off-policy deep reinforcement learning algorithm for Volt-VAR control in power dis-tribution systems. *IEEE Trans. Smart Grid* **2020**, *11*, 3008–3018. [CrossRef]
213. Wang, Y.; Mao, M.; Chang, L.; Hatziargyriou, N.D. Intelligent Voltage Control Method in Active Distribution Networks Based on Averaged Weighted Double Deep Q-network Algorithm. *J. Mod. Power Syst. Clean Energy* **2023**, *11*, 132–143. [CrossRef]
214. Sun, X.; Qiu, J. Two-Stage Volt/Var Control in Active Distribution Networks with Multi-Agent Deep Reinforcement Learning Method. *IEEE Trans. Smart Grid* **2021**, *12*, 2903–2912. [CrossRef]
215. Cao, D.; Zhao, J.; Hu, W.; Ding, F.; Huang, Q.; Chen, Z.; Blaabjerg, F. Data-Driven Multi-Agent Deep Reinforcement Learning for Distribution System Decentralized Voltage Control with High Penetration of PVs. *IEEE Trans. Smart Grid* **2021**, *12*, 4137–4150. [CrossRef]

216. Hu, D.; Ye, Z.; Gao, Y.; Ye, Z.; Peng, Y.; Yu, N. Multi-agent deep reinforcement learning for voltage control with coordinated active and reactive power optimization. *IEEE Trans. Smart Grid* **2022**, *13*, 4873–4886. [CrossRef]
217. Li, Y.; Hao, G.; Liu, Y.; Yu, Y.; Ni, Z.; Zhao, Y. Many-objective distribution network reconfiguration via deep reinforcement learning assisted optimization algo-rithm. *IEEE Trans. Power Deliv.* **2022**, *37*, 2230–2244. [CrossRef]
218. Kushwaha, A.; Gopal, M.; Singh, B. Q-Learning based Maximum Power Extraction for Wind Energy Conversion System with Variable Wind Speed. *IEEE Trans. Energy Convers.* **2020**, *35*, 1160–1170. [CrossRef]
219. Liu, H.; Wu, W. Federated Reinforcement Learning for Decentralized Voltage Control in Distribution Networks. *IEEE Trans. Smart Grid* **2022**, *13*, 3840–3843. [CrossRef]
220. Kang, H.-K.; Chung, I.-Y.; Moon, S.-I. Voltage control method using distributed generators based on a multi-agent system. *Energies* **2015**, *8*, 14009–14025. [CrossRef]
221. Molina-Garcia, A.; Bouffard, F.; Kirschen, D.S. Decentralized Demand-Side Contribution to Primary Frequency Control. *IEEE Trans. Power Syst.* **2011**, *26*, 411–419. [CrossRef]
222. Cheng, X.; Li, C.; Liu, X. A review of federated learning in energy systems. In Proceedings of the 2022 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Shanghai, China, 8–11 July 2022; pp. 2089–2095.
223. Mohandes, B.; El Moursi, M.S.; Hatziargyriou, N.; El Khatib, S. A review of power system flexibility with high penetration of renewables. *IEEE Trans. Power Syst.* **2019**, *34*, 3140–3155. [CrossRef]
224. Kabir, M.E.; Ghafouri, M.; Moussa, B.; Assi, C. A Two-Stage Protection Method for Detection and Mitigation of Coordinated EVSE Switching Attacks. *IEEE Trans. Smart Grid* **2021**, *12*, 4377–4388. [CrossRef]
225. Du, Y.; Li, F.; Kurte, K.; Munk, J.; Zandi, H. Demonstration of Intelligent HVAC Load Management with Deep Reinforcement Learning: Real-World Experience of Machine Learning in Demand Control. *IEEE Power Energy Mag.* **2022**, *20*, 42–53. [CrossRef]
226. Förderer, K.; Ahrens, M.; Bao, K.; Mauser, I.; Schmeck, H. Modeling flexibility using artificial neural networks. *Energy Inform.* **2018**, *1*, 21. [CrossRef]
227. Hu, Z.; Yao, W.; Shi, Z.; Shuai, H.; Gan, W.; Wen, J. Intelligent and rapid event-based load shedding pre-determination for large-scale power systems: Knowledge-enhanced parallel branching dueling Q-network approach. *Appl. Energy* **2023**, *347*, 121468. [CrossRef]
228. Zhang, B.; Hu, W.; Ghias, A.M.; Xu, X.; Chen, Z. Multi-agent deep reinforcement learning-based coordination control for grid-aware multi-buildings. *Appl. Energy* **2022**, *328*, 120215. [CrossRef]
229. Guelpa, E.; Verda, V. Demand response and other demand side management techniques for district heating: A review. *Energy* **2021**, *219*, 119440. [CrossRef]
230. Vázquez-Canteli, J.R.; Nagy, Z. Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Appl. Energy* **2019**, *235*, 1072–1089. [CrossRef]
231. Calero, F.; Cañizares, C.A.; Bhattacharya, K.; Anierobi, C.; Calero, I.; de Souza, M.F.Z.; Farrokhabadi, M.; Guzman, N.S.; Mendieta, W.; Peralta, D.; et al. A Review of Modeling and Applications of Energy Storage Systems in Power Grids. *Proc. IEEE* **2023**, *111*, 806–831. [CrossRef]
232. Wang, W.; Yuan, B.; Sun, Q.; Wennersten, R. Application of energy storage in integrated energy systems—A solution to fluctuation and uncertainty of renewable energy. *J. Energy Storage* **2022**, *52*, 104812. [CrossRef]
233. Wang, Y.; Wai, R.-J. Adaptive fuzzy-neural-network power decoupling strategy for virtual synchronous generator in mi-cro-grid. *IEEE Trans. Power Electron.* **2022**, *37*, 3878–3891. [CrossRef]
234. Kotb, K.M.; Elmorshedy, M.F.; Salama, H.S.; Dán, A. Enriching the stability of solar/wind DC microgrids using battery and superconducting magnetic energy storage based fuzzy logic control. *J. Energy Storage* **2022**, *45*, 103751. [CrossRef]
235. Bui, Y.-H.; Hussain, A.; Kim, H.-M. Double Deep $Q$$ -Learning-Based Distributed Operation of Battery Energy Storage System Considering Uncertainties. *IEEE Trans. Smart Grid* **2020**, *11*, 457–469. [CrossRef]
236. Shuai, H.; Li, F.; Pulgar-Painemal, H.; Xue, Y. Branching Dueling Q-Network-Based Online Scheduling of a Microgrid with Distributed Energy Storage Systems. *IEEE Trans. Smart Grid* **2021**, *12*, 5479–5482. [CrossRef]
237. Duan, J.; Yi, Z.; Shi, D.; Lin, C.; Lu, X.; Wang, Z. Reinforcement-learning-based optimal control of hybrid energy storage systems in hybrid AC–DC microgrids. *IEEE Trans. Ind. Inform.* **2019**, *15*, 5355–5364. [CrossRef]
238. Daneshvar, M.; Mohammadi-Ivatloo, B.; Asadi, S.; Zare, K.; Anvari-Moghaddam, A. Optimal Day-Ahead Scheduling of the Renewable Based Energy Hubs Considering Demand Side Energy Management. In Proceedings of the 2019 International Conference on Smart Energy Systems and Technologies (SEST), Porto, Portugal, 9–11 September 2019; pp. 1–6.
239. Daneshvar, M.; Mohammadi-Ivatloo, B.; Asadi, S.; Anvari-Moghaddam, A.; Rasouli, M.; Abapour, M.; Gharehpetian, G.B. Chance-constrained models for transactive energy management of interconnected microgrid clusters. *J. Clean. Prod.* **2020**, *271*, 122177. [CrossRef]
240. Daneshvar, M.; Mohammadi-Ivatloo, B.; Asadi, S.; Abapour, M.; Anvari-Moghaddam, A. A transactive energy management framework for regional network of microgrids. In Proceedings of the 2019 International Conference on Smart Energy Systems and Technologies (SEST), Porto, Portugal, 9–11 September 2019; pp. 1–6.
241. Akbari-Dibavar, A.; Daneshvar, M.; Mohammadi-Ivatloo, B.; Zare, K.; Anvari-Moghaddam, A. Optimal robust energy management of microgrid with fuel cells, hydrogen energy storage units and responsive loads. In Proceedings of the 2020 International Conference on Smart Energy Systems and Technologies (SEST), Istanbul, Turkey, 7–9 September 2020; pp. 1–6.

242. Daneshvar, M.; Mohammadi-Ivatloo, B. Overview of Internet of Things-based multi-energy management of cleaner multi-energy mix. In *InIoT Enabled Multi-Energy Systems*; Academic Press: Cambridge, MA, USA, 2023; pp. 1–8.
243. Taghizad-Tavana, K.; Kheljani, H.S.; Hosseini, S.H.; Tarafdar-Hagh, M.; Daneshvar, M. Multi-dimensional management of smart distribution networks: Comparative analysis of box and polyhedral methods for modeling uncertainties. *Sustain. Cities Soc.* **2024**, *108*, 105488. [CrossRef]
244. Safari, A.; Badamchizadeh, M.A. NeuroQuMan: Quantum neural network-based consumer reaction time demand response predictive management. *Neural Comput. Appl.* **2024**, *36*, 19121–19138. [CrossRef]
245. Sadeghian, O.; Safari, A. Net saving improvement of capacitor banks in power distribution systems by increasing daily size switching number: A comparative result analysis by artificial intelligence. *J. Eng.* **2024**, *2024*, e12357. [CrossRef]
246. Safari, A.; Kharrati, H.; Rahimi, A. A hybrid attention-based long short-term memory fast model for thermal regulation of smart residential buildings. In *IET Smart Cities*; Wiley: Hoboken, NJ, USA, 2024. [CrossRef]
247. Safari, A.; Kharrati, H.; Rahimi, A. Multi-term electrical load forecasting of smart cities using a new hybrid highly accurate neural network-based predictive model. *Smart Grids Sustain. Energy* **2023**, *9*, 8. [CrossRef]