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Review

AI-Driven Urban Energy Solutions—From Individuals to Society: A Review

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Abstract: This paper provides a comprehensive review of solutions based on artificial intelligence (AI) in the urban energy sector, with a focus on their applications and impacts. The study employed a literature review methodology to analyze recent research on AI's role in energy-related solutions, covering the years 2019 to 2023. The authors classified publications according to their main focus, resulting in two key areas of AI implementation: residential and individual user applications, and urban infrastructure integration for society. The objectives of this review of the literature are the following: O1: to identify trends, emerging technologies, and applications using AI in the energy field; O2: to provide up-to-date insights into the use of AI in energy-related applications; O3: to gain a comprehensive understanding of the current state of AI-driven urban energy solutions; O4: to explore future directions, emerging trends, and challenges in the field of AI-driven energy solutions. This paper contributes to a deeper understanding of the transformative potential of AI in urban energy management, providing valuable insights and directions for researchers and practitioners in the field. Based on the results, it can be claimed that AI connected to energy at homes is used in the following areas: heating and cooling, lighting, windows and blinds, home devices, and energy management systems. AI is integrating into urban infrastructure through the following solutions: enhancement of electric vehicle charging infrastructure, reduction in vehicle emissions, development of smart grids, and efficient energy storage. What is more, the latest challenges associated with the implementation of AI-driven energy solutions include the need to balance resident comfort with energy efficiency in smart homes, ensuring compatibility and cooperation among various devices, preventing unintended energy consumption increases due to constant connectivity, the management of renewable energy sources, and the coordination of energy consumption.

Keywords: energy; artificial intelligence; AI; smart city; smart home; smart grid; electric vehicle

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1. Introduction

In a rapidly evolving urban landscape, the challenges of energy consumption, sustainability, and efficiency remain critical concerns. The need for energy in cities is still growing and is related to the growing activities of residents, the need for advanced services, and the use of technical means in the city infrastructure. The last ones are connected with the Internet of Things and innovative solutions connected with energy in cities [1–3]. The Internet of Things (IoT) has ushered in a new era of urban connectivity and intelligence. In cities around the world, IoT technologies are revolutionizing the way urban infrastructure operates, providing an interconnected web of smart devices and sensors that collect and share data in real time [4]. These IoT systems allow city planners and administrators to gain unprecedented insight into various aspects of urban life, from traffic patterns [5], the use of different sources of energy [6–8] and energy consumption [9–11] to waste management [12] and air quality [13]. The pursuit of a ubiquitous Internet and the development of urban infrastructure means that the achievements of Industry 4.0 are being used on an increasingly larger scale, leading to more and more solutions based on smart elements [14,15] and neural networks [16]. One of the rapidly developing elements of the fourth industrial revolution is artificial intelligence (AI). Artificial intelligence is a transformative force fundamentally reshaping the way we live, work, and interact with our environment. It is important in the context of Industry 4.0 and the broader use of a ubiquitous Internet not only for entertainment [17] but also for regular everyday life. AI uses advanced algorithms, machine learning, and data analysis to mimic human cognitive functions, enabling machines to perceive, reason, and make decisions [18]. In cities, AI can be used to optimize energy infrastructure and create a more sustainable and resilient urban future. Artificial intelligence offers many solutions in various areas of human activity, including those used in the energy sector [19,20]. Some solutions are aimed at an individual resident, and others at the whole society. Nevertheless, AI-based solutions are the driving force towards a new intelligent society living in cities called smart cities.

As urban areas continue to expand and evolve, AI has become a critical tool for improving energy management, reducing carbon emissions, and improving the overall quality of life of urban residents. This paper presents a review of the literature of solutions driven by artificial intelligence that are or are planned or are in the study stage to be applied in the urban energy sector. Therefore, this article reviews and discusses the dynamic intersection of AI-driven solutions and the urban energy sector, providing a comprehensive review of the profound impact that AI technologies are having on cities around the world. The paper consists of six sections. Section 2 describes materials and methods. Sections 3 and 4 include AI-driven energy solutions, respectively, among residents/individual users and in urban infrastructure. Section 5 presents a discussion, and Section 6 summarizes the review.

2. Materials and Methods

The method used in this paper is literature review. The authors analyzed publications that describe research on AI-driven solutions connected with energy. In the first stage of the research, the authors used search engines including Web of Science and Scopus. The authors searched and reviewed published publications over the last five years, that is, from 2019 to 2023, to obtain the latest results of recent research on artificial intelligence and its application in energy-related solutions. The databases were used to search using two main keywords, which were 'artificial intelligence'/'AI' and 'energy'. It is worth noting that the authors entered the full name of artificial intelligence and its abbreviation into the search engine as separate searches. Additionally, the third keyword was added to each search—it was 'smart city', 'smart home', 'smart grid', and 'electric vehicle'. There were eight searches in total. The results of the search results in terms of the number of articles in each of the two databases—Scopus and Web of Science—are presented in Table 1. The largest number of articles were found in the Scopus database for the keywords 'artificial intelligence', 'energy', and 'smart grid' keywords.

Table 1. Search results for papers in Scopus and Web of Science depending on keywords.

Keywords	Number of Papers–Scopus	Number of Papers–Web of Science
Artificial intelligence, energy, smart city	127	22
Artificial intelligence, energy, smart home	58	15
Artificial intelligence, energy, smart grid	264	79
Artificial intelligence, energy, electric vehicle	132	30
AI, energy, smart city	26	9

Table 1. *Cont.*

Keywords	Number of Papers–Scopus	Number of Papers–Web of Science
AI, energy, smart home	10	4
AI, energy, smart grid	39	12
AI, energy, electric vehicle	18	4

Source: authors' own work.

For all of the papers found, the authors read abstracts and then chose all the papers that really fit the scope of the undertaken review on the set topic. Finally, the authors chose 153 papers that cover the topic of AI-driven urban energy solutions.

These publications were classified into these divisions based on their main focus or application areas within AI-driven urban energy solutions. Each category represents a specific aspect of how AI-driven energy solutions are implemented and utilized, including the following:

- Residential and individual user applications;
- Urban infrastructure integration for individual users and community oriented.

This categorization allows for a more structured analysis and understanding of the various applications and impacts of AI for urban energy. On the basis of the search results and analysis, the authors divided the mentioned parts into subsections. The first part includes five subsections, which include the following: heating and cooling, lighting, windows and blinds, home devices—refrigerators, and energy management systems. The second part was divided into four subsections including electric vehicle charging infrastructure, vehicle emission reduction, smart grid, and energy storages.

The main objectives of the literature review are the following:

- O1: To identify trends, emerging technologies, and applications using artificial intelligence in the energy field;
- O2: To provide up-to-date insights into the use of artificial intelligence in energy-related applications;
- O3: To gain a comprehensive understanding of the current state of AI-driven urban energy solutions;
- O4: To explore future directions, emerging trends, and challenges in the field of AI-driven energy solutions.

The research questions set in the study include:

- R1: What are the key emerging technologies in AI-driven energy solutions for residential users and society?
- R2: How is artificial intelligence integrated into urban infrastructure to enhance energy-related solutions?
- R3: What challenges are associated with the implementation of AI-driven solutions in urban energy management?

3. Residential and Individual User Applications for AI-Driven Urban Energy Solutions

3.1. Heating and Cooling

The first area that very often appears in research related to energy in residential buildings is heating and cooling devices, in other words, HVAC (heating ventilation and air conditioning) systems. These systems play a central role in regulating the indoor climate of homes, directly impacting both the comfort of inhabitants and energy consumption. Using artificial intelligence, innovative solutions are emerging to optimize heating and cooling processes, ensuring that homes remain comfortable while minimizing energy usage and environmental impact [21].

Heating in smart homes refers to the application of advanced technologies, including AI, to control and optimize the heating systems within residential buildings. In smart homes, heating systems are designed to be more energy efficient, convenient, and adaptable to individual preferences. AI-driven heating solutions can analyze data from various sources, such as weather forecasts and occupancy patterns, to make real-time adjustments to heating systems. For example, if a smart home detects that no one is at home during the day, it can lower the temperature to save energy and then start warming the house before the occupants return. These systems can be controlled remotely via smartphones or voice commands, allowing users to fine-tune their heating preferences. In general, AI-enhanced heating in smart homes aims to improve comfort while reducing energy consumption and costs. In the literature, there is different research on the topic of heating in smart homes. The authors of [21] develop a smart heater system characterized by high performance and low cost. It functions due to an open-source controller specially programmed with software that cooperates with the temperature and humidity sensor. The solution function via the cloud server that presents values measured using special application for smartphones. Due to this, users are able to remotely control the temperature (and the whole heating system) and schedule tasks via an application. One of the biggest advantages is that the solution reduces the risk of fire outburst. According to the authors, this solution provides safety, positively influences costs, and increases efficiency, performance, and useability. The authors of the paper [22] propose a different strategy of heating control, emphasizing the integration of user presence as an additional factor in managing heating within the living space. They present a flexible heating control system that adapts to diverse occupants within the heating network. Their method involves predicting heating dynamics using a multilayer perceptron neural network based on time series data. To manage the heating controller effectively, they employ a fuzzy inference system utilizing the Takagi–Sugeno model. In another paper [23], the authors present the IoT prototype that introduces a smart control approach named the smart token-based scheduling algorithm. It aims at optimizing energy in buildings' heating systems. The solution includes, among others, special hardware, software, networking. Other authors [24] present a novel residential energy management approach that reduces electricity consumption for space heating and battery connected to the grid. It achieves this without relying on pricing signals. The method employs a unique algorithm, integrating seasonal calculations and considering various factors such as temperature and photovoltaic (PV) generation.

In homes, smart thermostats with the function of real-time sensing are often used. They help minimize energy consumption and at the same time they maintain user comfort. There are different types of thermostats, for example, in residential buildings there are usually managed by reactive and heuristic-driven ones or by more advanced controls [25]. Advanced control systems in residential buildings have typically relied on either model-based approaches like model predictive control (MPC) [26] or model-free methods such as reinforcement learning (RL) [27,28] for their development. Today, more and more research is related to the development and scope of thermostat operation. Marantos et al. [29] in their research apply a smart thermostat concept which focuses mainly on cost reduction and deployment flexibility so they can be adopted on a big scale in many buildings and regions. Its idea integrates supervised and reinforcement learning to address the challenge of meeting occupants' thermal comfort requirements while minimizing energy usage. Goman and Koroloev [30] present the newest achievements on smart thermostats in and smart buildings. These devices can contribute to energy savings and control. The authors also describe prospects for the future which are self-learning algorithms for smart thermostats. According to them, it seems possible to develop a self-learning smart thermostat that is able to support a big building. Thermostats should follow and analyze user behavior and effect control at the level of a building and single rooms. Huang et al. [31] describe the work and function of a self-learning algorithm to predict indoor temperature and cooling demand from a smart Wi-Fi thermostat in a residential building. The dynamic model provided for any residence can be applied to guide residents when it comes to energy savings coming from set point schedule switches. Broader practical research is presented by Duman et al. [32] as the study combines a smart thermostat with a home energy management system (HEMS) for cost-effective load scheduling, demand response (DR), and photovoltaic self-consumption. The thermostat uses fuzzy logic to adjust set points based on electricity prices, solar radiation, and occupancy.

On the other hand, smart homes have cooling systems. Smart cooling systems use sensors to monitor temperature and humidity levels in various parts of the home and can automatically adjust the cooling settings to maintain the desired comfort level. These systems can also be controlled remotely via smartphones or voice-activated devices, allowing homeowners to customize their cooling preferences even when they are away from home. Additionally, AI-driven cooling systems can learn user preferences and adapt to daily routines, making them more energy-efficient by cooling or ventilating specific areas only when needed. It is worth noting, after [33], the significance of passive adaptive systems in the context of mode-switching for cooling and heating. Passive adaptive systems stand out for their ability to respond to environmental cues, such as changes in temperature or humidity, and autonomously shift between cooling and heating modes. Their capacity to adapt naturally, without requiring manual intervention, is a notable advantage. This not only streamlines their operation but also enhances their efficiency by ensuring that they can adjust to varying conditions, making them a promising choice for energy-efficient and user-friendly cooling and heating solutions. As we read in the paper of Daneshvar et al. [34], one of the innovative solutions within this topic is to provide a new cooling control approach as an element of the smart energy system that can achieve a balance between thermal comfort and building energy usage through the utilization of sensing and machine programming technology. To achieve this purpose, an overall form of a building must be coupled with this smart system, while the energy use with the thermal comfort cooling of people must be provided based on the special dedicated software. On the other hand, Nezhad et al. [35] present a new model for home energy management, considering inverter-based air conditioning and solar panels. The model aims to minimize daily electricity costs using time-of-use tariffs. It includes fixed and flexible loads and is formulated as a mixed-integer linear programming problem. The system uses a PV system and electrical energy storage to handle unpredictable solar power generation and optimize load management during peak hours. The air conditioning settings are adjusted based on an indoor-outdoor temperature model to reduce energy consumption and lower bills.

In the area of home heating and cooling, there is a very large potential for the use of artificial intelligence. For this reason, the authors have developed key directions for the future usage of AI in this area. Table 2 shows these key directions.

Table 2. Key directions for future usage of AI for heating and cooling in homes.

Direction	Description
Human-Centric AI	A focus on developing AI systems that prioritize user comfort and preferences, learning and adapting to individual user habits, creating personalized and user-centric experiences.
Advanced Control Algorithms	Research into advanced control algorithms, including reinforcement learning and predictive models, to optimize energy consumption and enhance user comfort, adapting to changing user behavior and environmental conditions.
Integration	The development of standardized protocols and interfaces for seamless integration of various AI-driven systems within smart homes, enabling better synergy and coordination between systems.
IoT and Sensor Technologies	Investment in the development of more sophisticated IoT devices and sensors for enhanced data collection and improved AI system performance, including better occupancy detection, environmental monitoring, and energy usage tracking.

Table 2. *Cont.*

Direction	Description
Energy Storage Integration	Exploring methods to integrate energy storage solutions, such as batteries, with heating and cooling systems to maximize the utilization of renewable energy sources (RES) and reduce grid dependence.
Accessibility	Providing AI-driven solutions accessible to a wide range of households, regardless of their size, location, or economic status, promoting inclusivity and adoption.
Sustainability	Investment in long-term research into the integration of renewable energy sources, such as solar and wind, with residential heating and cooling systems to promote sustainability and reduce the reliance on fossil fuels.

Source: Authors' own work based on: [21,23,24,33–39].

3.2. Lighting

Intelligent lighting control in a smart home context involves the use of advanced technologies and automation to manage and optimize lighting systems. Smart homes incorporate sensors, IoT devices, and AI to enhance the lighting experience for residents. These systems can automatically adjust lighting levels based on factors such as occupancy, natural light availability, and time of day. Like in the case of smart heating, users can remotely control their lighting via smartphone apps or voice commands. Moreover, intelligent lighting control in smart homes contributes to energy efficiency, making homes more sustainable, and improves the overall living experience by offering convenience and personalization. Smart lighting refers to lighting technology with an increased level of functionality such as dimming or remotely control the on/off button to enhance user comfort and save energy [40].

The authors of the paper [41] propose an intelligent lighting system designed for office environments, emphasizing cost-efficiency and environmental sustainability. The system is built around an Arduino microcontroller, infrared inductive sensors, and light sensors, with communication facilitated through a Wi-Fi network. The system's key functions include automatic control of delay, turn-off, and dimming of office lighting fixtures based on sensor readings, thereby enabling real-time detection and adjustment of the office lighting environment. By integrating these components, the system offers low-cost and environmentally friendly features tailored for office settings. Multiple sensors are strategically placed in the room and work in conjunction with the Arduino controller to detect various indoor parameters. The Arduino microcontroller acts as a data hub, receiving, processing, and transmitting the collected data through the communication network. It further displays this information on an LCD screen and uploads it to a client data center. One of the notable features of this intelligent lighting system is its automatic brightness adjustment, allowing users to achieve optimal lighting conditions at any given time. Moreover, users can remotely control lighting switches, adjust brightness, and activate predefined lighting scenes using a mobile application. This instantaneous feedback mechanism not only conserves energy when people leave the room but also enhances efficiency and provides users with real-time, comfortable illumination. In another paper [42], a comprehensive and functional prototype of an IoT-based lighting control system is introduced, with a primary focus on balancing natural and artificial lighting while incorporating a dynamic shading system. It provides a scalable approach to smart system integration within buildings, relying on sensing and actuating nodes (Arduino-driven) and a central unit (Raspberry Pi-driven). A dedicated control application is developed, allowing users to interact with the system by configuring automatic seasonal modes or manual settings. The system is designed to adjust the required illuminance threshold, with the shading system aligning itself with seasonal profiles based on bioclimatic design principles. Notably, the control system incorporates a fuzzy logic solution to ensure fast and responsive control without high computational demands. The overarching goals of this work encompass the development of a shading system for internal daylight intensity control, the design and construction of a versatile LED lighting system, the integration of shading and lighting into a unified prototype, the exploration of Arduino and single-board computers like Raspberry Pi for IoT control, and the creation of a user-friendly mobile application for configuring seasonal lighting and shading modes, illuminance thresholds, and manual settings. In another paper [43], the authors present a system designed to control lighting and electrical loads that takes advantage of embedded systems equipped with cost-effective wireless communication modules, which makes it suitable for a distributed and intelligent home automation architecture. The system integrates a range of sensors that facilitate the efficient use of electricity by automating tasks such as turning off lights and electrical devices while maintaining lighting regulation. Multiple modules communicate wirelessly with a central node, and user interaction is facilitated through a mobile application. The development and validation of the system involved using UML and Petri nets for design and modeling, while the implementation was carried out in C/C++ for 32-bit microcontrollers. Testing of the prototype demonstrated stable performance, fast communication, and sufficient coverage for a typical single-family house. Remarkably, the system's performance surpasses that of similar solutions found in the scientific community. The paper of Cho et al. [44] introduces a novel concept of lifelog-based smart lighting control, aiming to personalize lighting environments to match individual characteristics. While the potential for lifelogs to enable personalized lighting has long been recognized, the lack of data collection and synthesis methods has been a barrier. In this study, the authors propose lifelog data collection methods and an analytical approach to recommend custom lighting environments. They deploy sensors, lighting controllers, and control interfaces in a mock-up space and connect these to a machine learning server in the cloud. The platform they establish utilizes emotional, activity, and environmental lifelog data to create a truly personalized lighting experience. This innovative approach opens new possibilities for enhancing user comfort and well-being through lighting controls. It is worth mentioning also the results of the research of Ayan and Turkey [40] on smart LED bulbs as parts of smart lighting systems. This research presents the influence of using these bulbs on energy efficiency. The subject of the study was power consumption depending on different colors emitted by these bulbs. According to the results, the different colors have different power usage. In addition, case studies including detailed comparison between (1) halogen, (2) CFL, (3) LED, and smart LED were considered in the context of energy savings. It was proven that a smart LED consumes the least energy among other bulbs but solely when dimmed and under remote control.

Different scenario for lights, but also at the same time for alarms, is presented by Ozeer et al. [45]. The authors describe two key user stories that have been implemented as part of their study. The first scenario, termed the "Bedtime Scenario," involves a button press in the bedroom, signaling the house tenant's intention to go to bed. Subsequently, all lights are turned off and the alarm is set. If any motion is detected in the living room or the kitchen or if the door is opened, an alarm is triggered on a speaker, and the house's lamps are illuminated in red to indicate potential intruders or disturbances. The second scenario, referred to as the "Welcome Home Scenario," is initiated when the home tenant arrives at the front door. The Wemo motion sensor reports motion, and, in response, the lamp at the entrance is turned on, letting the person to unlock the door. When entering the house, the living room lamp is also turned on and a welcoming sound is played on the speaker to create a welcoming atmosphere. The paper suggests that these scenarios are only the beginning and that more complex scenarios can be orchestrated by their system based on patterns of events sensed and actuated, offering enhanced automation and convenience for users. Another paper [46] also presents the solution that combines smart lighting with other functions of a smart home. The framework proposed by the authors has versatile applications, including automated burglar alarm systems, guest attendance monitoring, and light switches. With the use of IoT solutions, these systems enable real-time monitoring and connectivity to central systems for automated burglar alarms. The monitoring framework is designed as a web application, providing real-time display, storage, and alerting functions for both local and remote monitoring control. Importantly, the monitoring system is described as stable and reliable when utilizing the SHA-256 authentication method. The system comprises three core components: hardware nodes, a secure server, and a web application. The IoT node hardware is designed for real-world testing and receiving IoT data from diverse devices. A dedicated server is established to monitor the IoT nodes within the system. Lastly, a user-friendly application is developed, accessible via smartphones or web browsers over Wi-Fi, enabling real-time control of the IoT smart system. Figure 1 shows the block diagram of the proposed smart lighting system.

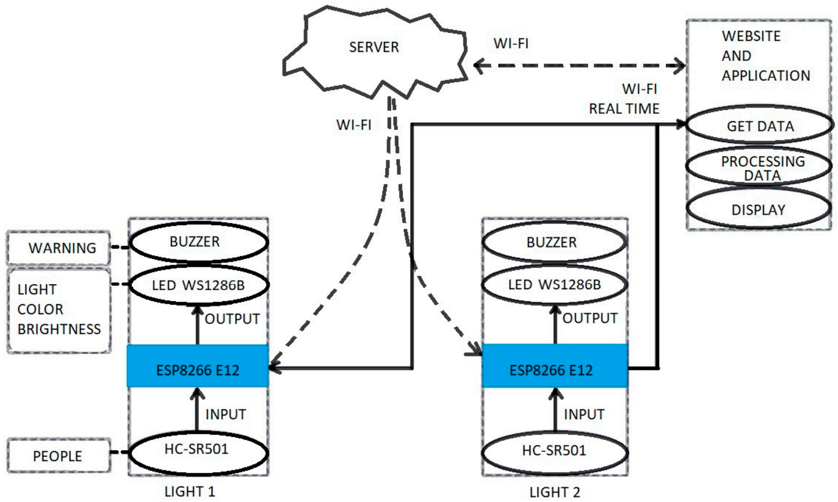

Figure 1. Block diagram of the smart lightning system—own work based on [46].

Summing up, when it comes to empirical findings related to specific implementations of AI models for lighting control within residential settings, the literature [40–42,44–47] presents the following: sensor-based adaptive lighting, natural light integration, personalized lighting scenes, dynamic lighting control, voice-controlled lighting systems, predictive lighting adjustments, and context-aware lighting. These examples showcase how AI models can be practically implemented in lighting controls within residential environments, offering diverse functionalities to enhance energy efficiency, user comfort, and the overall living experience.

It is also worth explaining in detail one of the mentioned examples. The "Bedtime Scenario" [45] in the smart home application for light automation and intrusion detection involves several software entities and devices working together to facilitate actions based on specific triggers:

- Button press: when a button in the bedroom is pressed, the "NodeHueSense" software entity reports this event from the Hue buttons and publishes it on the MQTT bus.
- Event subscription: the "Orchestrator" software subscribes to all events published in the MQTT Broker. In this scenario, it identifies the button press event from the bedroom.
- Scenario definition: the Orchestrator defines a specific scenario based on this event, triggering a sequence of actions in response. It sends messages to other software entities according to the predefined scenario.
- Light control: the "NodeHueActuate" entity receives messages from the Orchestrator to control the Hue lamps. In the bedtime scenario, it turns off all the lights in the house.
- Alarm setting: the scenario triggers an alarm setup, which might involve sending a signal to the "SoundPlayer" entity, instructing it to activate the speaker and set an alarm sound.
- Intrusion detection: if any motion is detected in certain areas or if the door is opened, the "FibaroAdapter" and "WemotionSense" report these events on the MQTT bus. The Orchestrator, based on this information, can trigger an alarm on the speaker and illuminate the house's lamps in red as a signal of potential intruders or disturbances.

This scenario showcases the coordination among various software entities and devices, orchestrated by the "Orchestrator" based on specific events, such as the button press, to automate actions like turning off lights, setting alarms, and responding to potential intrusions or disturbances.

For the topic of lighting and AI, the authors have developed the key directions. They are presented in Table 3.

Table 3. Key directions for future usage of AI for lighting in homes.

Direction	Description
Human-Centric AI	Development of lighting solutions aligned with rhythms and individual user preferences (including for example different lighting for bedtime and welcome home routines).
User-Friendly Control Interfaces	Designing intuitive mobile applications and voice-activated controls to enable users to customize their lighting environments with ease.
Web Applications and Remote Control	Development of user-friendly web applications and remote-control options to provide users with convenient access to their smart lighting systems from various devices.
Integration	Further development aimed at integration of AI-driven smart lighting systems with other smart home devices.
Personalized Lighting Experiences	Advancements in AI algorithms that adapt lighting conditions based on user preferences, promoting enhanced user comfort and well-being.
Sensing and IoT Advancements	Continued investment in sensor and IoT technologies to enhance occupancy detection, light level adjustments, and environmental monitoring, resulting in more responsive and energy-efficient lighting control.

Source: Authors' own work based on: [40–42,44–47].

3.3. Windows and Blinds

Another element of smart homes are smart windows. Smart windows for homes are an innovative technological solution designed to improve energy efficiency, comfort, and convenience [48]. These windows are equipped with various features and technologies that allow them to adapt to changing environmental conditions and user preferences. Special systems for smart windows offer a way to improve energy efficiency in the construction sector, in residential or commercial buildings. These systems can dynamically adjust the spectral properties of window glazing, controlling how it interacts with visible and infrared light [49]. This adaptability allows better management of solar radiation, resulting in significant energy savings, especially in regions where cooling is a primary concern. Additionally, smart windows optimize the use of natural daylight within buildings, improving visual comfort. In the literature, there is not so much research on smart windows; however, there are some studies on electrochromic materials used in smart windows. Electrochromic glass operates as an electric battery with thin films of specific materials [49]. The level of optical transparency in this glass is similar to the charge level in a battery. An essential element in electrochromic devices is the electrolyte, which conducts ions while insulating electrons. Electrolytes in these systems can be in liquid, gel, or solid form. Liquid electrolytes can be prone to leakage or evaporation if they contain solvents. Common ions transported through the electrolyte when an external voltage is applied are typically hydrogen and lithium, with occasional use of sodium. The electrochromic materials in these devices are predominantly transition-metal oxides and organic compounds. This material and function of smart windows is studied, for example by Ke et al. [50], Wang et al. [51], and Zhang et al. [52]. Some papers discuss smart hydrogel windows, such as [53–56]. In the literature, there are also review papers on the topic of smart windows, such as Aburas et al. [57], Nundy [58], and Tällberg et al. [59].

In terms of smart windows, it is justified to mention smart blinds. Smart blinds are window coverings that can be remotely controlled, typically through a smartphone app or voice commands. They offer convenience by allowing users to adjust the blinds' position, either opening or closing them, without needing to be physically present. Smart blinds can integrate with smart home systems, enabling automated schedules based on time of day or sunlight conditions. Some models are also capable of blocking out light to enhance privacy, regulate room temperature, and save energy. They provide a modern and efficient solution for light control in homes. In practice, however, when it comes to recent years, there are even fewer articles in the literature about intelligent blinds than articles about intelligent windows. In an example, in the paper of Jung et al. [60], smart windows combined with photovoltaics blinds and a ventilation system was proposed. Similar research on PV blinds are discussed in [61,62].

The key directions developed by the authors for usage of AI for blinds and windows are presented in Table 4.

Table 4. Key directions for future usage of AI for blinds and windows in homes.

Direction	Description
Energy Efficiency	Advancements in AI-based technologies to improve the energy efficiency of smart windows and blinds, enabling better management of solar radiation and enhancing insulation, especially in regions with varying climate conditions.
User-Friendly Control Interfaces	Development of intuitive user interfaces, such as smartphone applications and voice-activated commands, to improve user convenience and control over smart blinds and windows.
Web Applications and Remote Control	Enhancing remote control features for smart blinds, ensuring that users can adjust them even when they are away from home, contributing to energy savings and security.
Integration	Research on integration of smart windows and blinds with broader smart home systems to allow synchronized automation
Advancements in Materials	Ongoing research on electrochromic materials for smart windows, exploring their properties, durability, and environmental impact, with the aim of making them more accessible and effective.
PV	Research into the integration of photovoltaic blinds with smart window systems to harness solar energy and improve energy sustainability in buildings.

Source: Authors' own work based on: [48,49,57–62].

3.4. Home Devices–Refrigerators

According to Wang et al. [63], daily, a significant amount of food is needlessly discarded due to prolonged storage in refrigerators, resulting in environmental strain. Refrigerators themselves are energy-intensive appliances, and minimizing refrigerator door openings could substantially contribute to environmental preservation. Hence, the authors in their research use the (r,n)-threshold SIS scheme to develop picture-sharing technology and introduce a series of smart refrigerator designs. This incorporates food identification technology, enabling users to promptly identify available ingredients on the smart fridge's display. This innovative approach minimizes food waste and conserves energy consumption. Other authors [64] in their research proposed a hardware upgrade for smart home refrigerators. They designed a Wi-Fi-enabled main control board that maintains compatibility with existing components. They implemented a simple learning algorithm on the microcontroller to optimize system efficiency while ensuring food safety temperatures or user preferences. Additionally, they introduced a wireless sensor node to provide accurate food temperature data for precise monitoring and control. The results demonstrate a significant efficiency improvement, with an enhancement in the refrigeration cycle and an improvement in the defrost cycle. Another paper [65] analyzed the energy efficiency of IoT-controlled refrigerators. The authors explored the impact of different temperature hysteresis bands and the presence of internal products on the energy consumption of household refrigerators using an IoT-controlled system. It reveals that larger hysteresis bands lead to increased energy use when the fridge is empty, but the opposite is true when there is an internal product (more thermal mass). By choosing the right hysteresis band based on the product's characteristics, potential energy savings of up to 20% are achievable. Achieving this efficiency requires a real-time adaptation scheme that identifies the refrigerator's underlying dynamics and control, as described in the paper. For larger-scale refrigeration systems, such as those in superstores, employing IoT as demonstrated in the paper enables candidate algorithms for demand-side management (DSM) and real-time hysteresis band adjustments to accommodate product mass changes. Some other authors from the study from this year (2023) conducted a SmartFridge project as a study toward environmental sustainability and the economy. In their paper [66], they evaluated a refrigerator model in terms of its energy consumption, considering factors such as indoor temperature and moisture. The results of their study show that as the indoor temperature increases, energy consumption increases. Moisture has a minor impact on the energy use of the refrigerator, according to simulation data. The choice of interior temperature also significantly affects energy consumption. Table 5 shows the key directions for AI-driven refrigerators.

Table 5. Key directions for future usage of AI for refrigerators.

Direction	Description
Energy Efficiency	Developing energy-efficient algorithms and control boards to optimize refrigerator performance, reduce energy consumption, and lower environmental impact. AI can optimize the cooling cycles of the refrigerator based on factors such as the outside temperature, usage patterns, and the contents of the refrigerator. This dynamic adjustment ensures that the refrigerator does not work harder than necessary, reducing energy consumption.
IoT-Enabled Temperature Control	Exploring IoT-controlled refrigerators to optimize energy use based on the presence of internal products.
Predictive Maintenance	Smart refrigerators use AI to monitor their own performance and detect early signs of malfunctions or maintenance issues. By identifying problems in advance, they can schedule repairs or maintenance during low-demand periods, preventing sudden breakdowns that might lead to energy waste
Integration	Smart refrigerators can be integrated into larger home energy management systems, allowing homeowners to coordinate the operation of various smart appliances, heating and cooling systems, and lighting to maximize energy efficiency throughout the home.
PV	Research on the development of solar PV-powered refrigerators.

Source: Authors' own work based on [63–69].

3.5. Energy Management Systems

In residential buildings, AI-driven systems are becoming increasingly important for managing energy consumption. As homes consume more electricity and incorporate distributed energy sources, there is a growing focus on optimizing the expenses related to purchasing electricity for household users. There are different systems and approaches to energy management in homes described in the literature. Some authors name these systems a smart energy management system (SEMS), some call it a home energy management system (HEMS), and others just call it an energy management system (EMS), as it is described below. Figure 2 shows an example of a home energy management system [70]. The aim of the system with various household appliances is to optimize their energy usage. This system is connected to a service provider through a bidirectional communication network, enabling the exchange of pricing and appliance energy consumption data. The EMS receives hourly pricing information from the service provider and adjusts the energy consumption of each appliance in response to these prices. Typically, household electric appliances are categorized into three main types based on their characteristics and priorities: non-shiftable, shiftable, and controllable loads.

The previously mentioned paper of Duman et al. [32] also present the study of a home energy management system (HEMS). The HEMS schedules time-shiftable loads, including battery storage and electric vehicles, while considering bi-directional power flow and battery degradation. It is worth noting that electric cars become more and more popular when it comes to research [71–73], and, therefore, homes also have started to have charging stations for them. Simulation results indicate a cost reduction under time-of-use and a reduction in air conditioning (AC) costs. Homeowners input occupancy, AC settings, appliance usage windows, hot water schedule, and electrical vehicle (EV) charging preferences. The utility sends energy prices, demand response, and weather forecasts. A smart thermostat adjusts AC settings based on solar radiation, electricity prices, and occupancy. The home energy management system optimizes load scheduling, considering bidirectional power flow and battery health to minimize costs and enhance self-consumption.

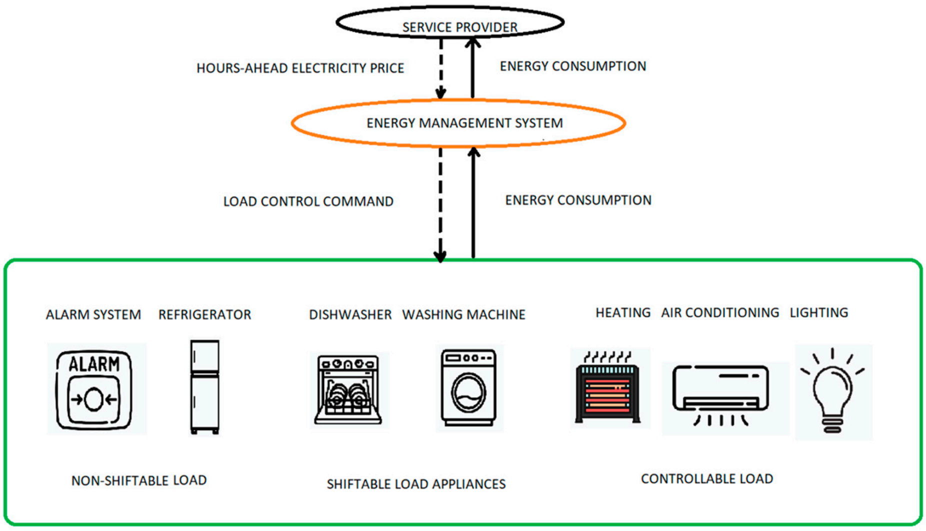

Figure 2. An example of home energy management system—own work based on [70].

Ma et al. [74] describe a HEMS model designed to optimize the energy usage in homes. It takes into account various factors including household devices, distributed energy sources, energy storage, and electric vehicle charging. HEMS is a self-regulating system that can adapt to changes in electricity prices and consumption. It controls the energy for different devices such as air conditioners, water heaters, washing machines, electric vehicle chargers, and others. Chauhan et al. [75] present research on the cost reduction using a smart energy management system. SEMS reduces energy waste, cost, and electricity bills without compromising user comfort. To test SEMS, a residential microgrid system with smart appliances, photovoltaic panels, and energy storage is evaluated under flat and real-time pricing. The results indicate energy savings and a reduction in electricity costs. The SEMS's innovative scheduling and cost-driven appliance management demonstrate its novelty and effectiveness. It must be noted that PV installations are increasingly popular among individuals [76,77]. The authors of [78] present the study on a smart energy system that uses machine learning algorithms. These techniques can autonomously regulate heating and hot water systems, which are major energy consumers in households. This not only helps reduce energy usage, but also enhances comfort for residents. With the growing adoption of renewable energy sources in homes, coordinating energy consumption with production becomes crucial for additional savings and reducing peak loads. The authors propose the development of a deep reinforcement learning (DRL) algorithm for controlling indoor and hot water temperatures to optimize energy consumption by leveraging solar energy production. Additionally, they also introduce a method for dynamically setting indoor temperature preferences, offering greater flexibility and energy savings. Other authors [79] introduce a novel approach that combines three distinct artificial intelligence techniques to address energy demand planning in smart homes. Designed as a multi-objective scheduling problem, this method seeks a balance between energy cost and user comfort. By utilizing an elitist non-dominated sorting genetic algorithm II, it incorporates demand-side management that considers factors like electricity price variations, equipment priority, operational cycles, and energy storage. Additionally, it includes a distributed generation forecast using support vector regression for the next day. It is worth mentioning that there are also many review articles from 2023 (the newest) on the topic of energy management systems in homes, for example [80–83]. Table 6 shows the key directions for AI-driven refrigerators.

Table 6. Key directions of usage of AI for home energy management systems.

Direction	Description
Energy Efficiency	Development of advanced AI algorithms that can optimize energy usage in homes. This includes predicting energy demand, dynamically adjusting energy sources, and prioritizing energy consumption based on user preferences and real-time data.
Real-Time Energy Monitoring	Development of AI-driven systems for real-time monitoring of energy consumption and production within homes. This can involve the use of sensors and IoT devices to gather data and AI algorithms to provide insights and recommendations.
Predictive Maintenance	The use of AI to predict maintenance needs for home energy systems, such as heating, cooling, and renewable energy installations.
Demand Response and Grid Integration	The development of ways in which AI can facilitate demand response mechanisms, enabling homes to interact with the broader energy grid more intelligently. AI can help homes respond to grid signals and optimize energy consumption during peak and off-peak hours.
Energy Source Integration	The development of ways in which AI can facilitate the integration of diverse energy sources, such as solar panels, wind turbines, and battery storage, into home energy systems.
Human-Behavior Integration	Research on how AI can effectively integrate with human behavior in homes. This involves understanding how occupants interact with energy systems and developing AI solutions that adapt to users' energy-related habits and preferences.

Source: Authors' own work based on [32,70,74,75,78–80,84–86].

4. Urban Infrastructure Integration of AI-Driven Energy Solutions

4.1. Electric Vehicle Charging Infrastructure

Artificial intelligence plays an increasingly important role in electric vehicle charging infrastructure to enhance its efficiency, reliability, and user experience [87]. AI algorithms can analyze various factors such as the grid load, energy prices, and individual user preferences to create optimal charging schedules for EVs [88]. This ensures that charging occurs during periods of lower energy demand or when renewable energy sources are abundant, reducing costs and the environmental impact [89]. Also, AI can facilitate demand response programs, allowing EV owners to participate in load-shifting initiatives. During peak demand periods, AI can coordinate with users to temporarily reduce their charging rates, alleviating stress on the grid and helping to prevent blackouts [90].

El Husseini et al. [91] discuss the integration of blockchain and AI technologies as a solution to address these challenges. It suggests that combining these technologies can lead to a more secure, efficient, and decentralized charging ecosystem. They discuss a couple of use cases where AI and blockchain technologies complement each other to enhance the charging infrastructure for EVs [88,92]. These use cases likely illustrate scenarios where technologies work together to improve security and optimize charging schedules. According to this research, it is intended to help stakeholders identify potential directions and implementations for better charging systems for EVs. This implies that the paper aims to inform decision-makers about the possibilities and advantages of integrating AI and blockchain in the EV charging infrastructure [93].

Chaihoie et al. [94] points out that to prepare an appropriate predictive model for charger planning, AI usage is very useful. They described the "predict-then-optimize" approach, where AI is used to predict the EV charging demand. This prediction is made using a multi-relation graph convolutional network (GCN)-based encoder–decoder deep architecture. This predictive model allows for more data-driven planning and allocation of resources. In the describe approach, AI is also utilized to optimize the competitive resource allocation strategy for charger planning. This likely involves determining where to place charging stations and how to distribute them effectively to meet anticipated demand. AI can be used to address the optimal size of EV chargers, determining the number of chargers that each service provider should deploy in various areas of the city.

Another complex analysis on AI usage in context of electric vehicle charging infrastructure was described by Qin and Folly [95]. They pointed out that AI, particularly deep learning methods like LSTM and GRUs, can be useful for forecasting EV charging and discharging patterns. The paper highlights the importance of accuracy in forecasting models, considering the stochastic and unpredictable nature of EV charging patterns. It also mentions the use of hybrid and ensemble techniques to improve forecast accuracy.

Dynamic pricing strategies are crucial to influence EV owners' charging and discharging behaviors. The paper discusses the challenges of existing dynamic pricing models, such as undervaluing or overvaluing stored battery power. It suggests the need for pricing models that reflect real-time power system conditions and balance the interests of system operators and EV owners. The AI can be used to achieve this dynamic pricing approach.

Also, the AI can be useful in the development phase of vehicle-to-grid (V2G). The development of V2G can be categorized into three phases [96]. In the first phase, the EV charging load is a small proportion of the power grids, mainly using uncontrolled and controlled charging strategies. The second phase sees an increased EV charging load with the high penetration of EVs, necessitating smart charging/discharging control strategies and aggregator coordination. The third phase envisions a mature state in which many EVs provide ancillary services to power grids [97].

Another possible application of AI in vehicles charging infrastructure was described by Mosayebi et al. [98]. The authors describe the need for improved charging infrastructure for electric vehicles as a result of their increasing numbers worldwide. It introduces the concept of a smart extreme fast portable charger (SEFPC) for EVs with multiple input sources, including the power grid and renewable energy sources such as an energy storage system (ESS). The SEFPC is designed to optimize the charging process by considering available power sources and the condition of the EV battery to save energy and time. A machine learning algorithm, based on IT, specifically a model-free sliding mode controller, is applied to determine the optimal charging operation mode based on the state of the battery and power source conditions. This approach aims to enhance battery life and overall system efficiency. The text concludes by mentioning real-time results obtained using the OPAL-RT platform to validate the effectiveness and feasibility of the SEFPC and the model-free sliding mode controller.

The very important problem in the case of charging infrastructure is connected with the importance of effectively placing charging stations to support the growth of EVs and enhance the traffic network's efficiency. Existing research often focuses on EV users' mileage anxiety but overlooks their strategic and competitive charging behaviors. According to Lazari and Chassiakos et al. [99], to address this issue, the concept of charging cost for an EV user can be introduced, considering factors such as the cost of traveling to access charging stations and the cost of queuing at charging stations. The problem can be formulated as the charging station placement problem (CSPP), initially as a bilevel optimization problem. It then leverages the equilibrium of the EV charging game to convert the problem into a single-level optimization task, proposing the "Optimizing eleCtric vEhicle chArging statioN" (OCEAN) algorithm for optimal charging station allocation. Recognizing OCEAN's scalability limitations, a heuristic algorithm based on AI called OCEAN can be used with continuous variables to handle large-scale real-world scenarios. The results of extensive experiments demonstrate that their approach significantly outperforms baseline methods in addressing the competitive and strategic charging behaviors of EV users.

Artificial intelligence profoundly impacts EV charging infrastructure, optimizing charging schedules based on grid load, energy prices, and user preferences. Studies propose integrating AI with the blockchain to enhance the security, efficiency, and decentralization of EV charging ecosystems. Predictive AI models aid in anticipating EV charging demand, facilitating data-driven planning, resource allocation, and optimal sizing of charging stations. AI-driven deep learning methods like LSTM and GRUs enhance accuracy in forecasting EV charging patterns, which is crucial for dynamic pricing strategies and vehicle-to-grid development. Additionally, the concept of a smart extremely fast portable charger utilizes AI to optimize charging considering various input sources and EV battery conditions. In Table 7, there is a comparison of the advantages and disadvantages of AI usage in electric vehicle charging infrastructure.

Table 7. Advantages and disadvantages of AI usage in electric vehicle charging infrastructure.

Advantages	Disadvantages
Efficient charging scheduling to reduce grid strain during peak hours.	Initial setup and integration costs can be high.
Accurate range prediction for improved trip planning.	Dependence on AI technology, which may have downtime or errors.
Reduced grid congestion and load balancing.	Privacy concerns related to data collection and monitoring of user behavior.
Smart charging infrastructure for a better user experience.	Potential job displacement in traditional charging station maintenance.
Energy cost optimization for cost savings.	Concerns about cybersecurity and data protection.
Battery management to extend battery life.	Need for continuous updates and maintenance of AI systems.
Predictive maintenance to reduce the downtime of charging stations.	Possible resistance or skepticism from users unfamiliar with AI technology.
Adaptive charging rates for efficient charging.	Environmental impact and sustainability concerns related to energy sources.
Improved user experience with real-time information and remote management.	Challenges of integration in existing infrastructure and grid systems.
Grid integration for V2G services and grid stability.	Complexity in regulating and standardizing AI usage in the industry.

Source: Authors' own work on basis: [87–89,91,95,98,100–108].

The most important direction for the future usage of artificial intelligence in electric vehicle charging infrastructure are summarized in Table 8.

Table 8. Key directions for future usage of AI in electric vehicle charging infrastructure.

Direction	Description
Smart Grid Integration	Integrate AI with the smart grid to balance energy supply and demand, optimize charging schedules, and support bidirectional charging for grid stability.
Dynamic Charging Station Placement	Use AI to identify optimal locations for new charging stations based on traffic patterns, EV adoption rates, and local energy infrastructure.
Predictive Maintenance	Using artificial intelligence for predictive maintenance of charging stations to reduce downtime and ensure reliable service, including monitoring components such as connectors and power electronics.
User-Centric Charging Services	Develop AI-driven apps and services that offer personalized charging recommendations, payment solutions, and real-time station availability information.
Energy Management and Cost Optimization	Implement AI to manage energy costs, ensuring that charging stations use electricity at the most cost-effective times while considering renewable energy sources.
Vehicle-to-Grid (V2G) Integration	Enable V2G capabilities with AI to allow EVs to feed surplus energy back to the grid, reducing peak demand and earning rewards for vehicle owners.
Fleet Charging Solutions	Create AI-powered solutions for fleet managers to optimize charging schedules, monitor vehicle health, and reduce operational costs of electric vehicle fleets.
Interoperability and Standardization	Establish AI-driven standards that ensure interoperability between different charging networks, vehicle models, and manufacturers, promoting EV adoption.
AI-Enhanced DC Fast Charging	Improve DC fast charging technology with AI to manage high-power charging, battery safety, and thermal management for shorter charging times.
Energy Storage Integration	Incorporate energy storage systems at charging stations and use AI to manage energy flow, enhancing the resilience of the charging station and grid support.

Table 8. *Cont.*

Direction	Description
Adaptive Load Management	Implement AI algorithms for adaptive load management that balance energy distribution among multiple charging stations, minimizing grid strain.
User Behavior Analytics	Analyze user behavior with AI to understand charging patterns, preferences, and peak usage times to optimize station planning and energy management.
Real-time Grid Health Monitoring	Use AI for real-time monitoring of the electric grid's health, identifying vulnerabilities and proactively addressing issues to ensure charging station reliability.
Environmental Impact Assessment	Develop AI models to assess the environmental impact of EV charging infrastructure and inform decisions regarding its expansion and sustainability.
Security and Fraud Detection	Enhance cybersecurity with AI to protect charging stations from hacking and fraud, protecting user data and financial transactions.
Education and Awareness Initiatives	Utilize AI for educational campaigns and awareness initiatives to inform the public about the benefits of EVs and the accessibility of the charging infrastructure.

Source: Authors' own work based on: [87–89,91,95,96,98,100–109].

4.2. Vehicle Emission Reduction

One of the promising technological advances in this effort is the application of artificial intelligence to mitigate vehicle emissions. AI is revolutionizing the automotive industry by enhancing the efficiency of conventional vehicles, accelerating the adoption of electric and hybrid vehicles, and optimizing traffic management. This two-page essay explores the multifaceted role of AI in vehicle emissions reduction [110].

One of the primary ways that AI contributes to vehicle emission reduction is by optimizing the performance of traditional internal combustion engines. AI algorithms are integrated into the engine control systems, enabling real-time monitoring and the adjustment of parameters to minimize emissions while maintaining efficiency [111]. These AI-driven systems take into account factors such as engine temperature, load, and fuel–air mixture to ensure that combustion is as clean and efficient as possible. By constantly adapting to changing driving conditions, these AI systems can significantly reduce harmful emissions.

According to Zhao et al. [112], the research of electric vehicles equipped with artificial intelligence has the capacity to significantly mitigate air pollution and carbon emissions. AI assistance enables these vehicles to operate more efficiently and make real-time decisions, contributing to a cleaner environment. By optimizing energy consumption and reducing the carbon footprint, AI-assisted electric vehicles offer a promising solution to combat the environmental challenges associated with conventional vehicles.

The rapid growth of electric and hybrid vehicles is a key strategy for reducing emissions [113]. AI plays an important role in the development and operation of these cleaner alternatives. For instance, AI is used to manage the power distribution in hybrid vehicles, deciding when to use electric or gasoline power based on driving conditions. It optimizes battery performance, expanding the range of electric vehicles [114].

Abduljabbar et al. [115] state that artificial intelligence is seen as a well-suited solution to address the complex challenges faced by transportation systems, including growing travel demands, rising CO_2 emissions, safety issues, and environmental degradation. These challenges are a direct result of the continuous expansion of traffic, both in rural and urban areas, driven by population growth, especially in developing countries. For instance, in Australia, the cost of congestion is projected to rise to 53.3 billion as the population increases to 30 million by 2031. In Melbourne, Australia, alone, over 640 km of arterial roads experience congestion during peak hours, leading to an annual CO_2 emission of 2.9 tons.

AI-driven eco-driving assistants provide real-time feedback to drivers on how to optimize their driving habits for better fuel efficiency and lower emissions [116]. These systems analyze data from various vehicle sensors, including engine performance, speed, and fuel consumption, to advise drivers on the most fuel-efficient speeds, optimal gear shifting points, and efficient acceleration and braking patterns [117]. By following these recommendations, drivers can significantly reduce their carbon footprint, and over time, this has a collective impact on emissions reduction and ensures a seamless transition between electric and internal combustion modes [118]. These assistants also incorporate route optimization, suggesting the most efficient routes to reach a destination. By avoiding traffic congestion and stop-and-go driving, vehicles can operate more efficiently, resulting in reduced emissions [119].

Delnevo et al. [120] explored the integration of big data and machine learning to forecast when the friction brake will be activated. The objective is to enhance energy efficiency in electric vehicles, raise driver awareness, and alleviate concerns related to 'range anxiety.' Subsequently, the in-vehicle human–machine interface can take advantage of these real-time predictions to provide drivers with more precise and comprehensive insights into their braking habits, ultimately promoting eco-friendly driving practices.

Also, an AI-based solution can be useful in optimizing traffic flow and reducing congestion, which, in turn, can lead to emissions reduction. AI-powered traffic management systems use real-time data from various sources, including traffic cameras, sensors, and smartphones, to analyze traffic patterns [121]. These systems can adjust traffic signals, suggest alternate routes, and even implement dynamic toll pricing to reduce congestion during peak hours [122].

In the 21st century, numerous researchers [110,113,122–124] are striving to establish a more reliable transportation system that minimizes its impact on people and the environment, while remaining cost-effective and efficient through the application of AI techniques. AI holds significant promise for enhancing various aspects of transportation, including road infrastructure, driver assistance, road user experience, and vehicle operation.

Summing up, artificial intelligence demonstrates a pivotal role in curbing vehicle emissions by optimizing traditional combustion engines in real time. These AI-integrated systems meticulously adjust parameters, like engine temperature and fuel–air mixtures, to substantially minimize harmful emissions while ensuring efficiency, thereby showcasing promising results in emission reduction. Additionally, AI plays a vital role in enhancing electric and hybrid vehicles' efficiency by managing power distribution, extending battery range, and offering real-time decision-making capabilities, thereby significantly reducing the environmental impact. AI-enabled eco-driving assistants provide personalized feedback to drivers, optimizing driving habits for fuel efficiency and lower emissions by advising on optimal speed, gear shifting points, and efficient acceleration patterns. Furthermore, AI-based traffic management systems leverage real-time data to optimize traffic flow, reduce congestion, and subsequently cut down on emissions during peak hours. These implementations underscore AI's effectiveness in mitigating emissions and optimizing transportation systems.

Some key directions for the future usage of artificial intelligence in vehicle emission reduction are presented in Table 9.

Table 9. Key directions for future usage of AI in vehicle emission reduction.

Direction	Description
Real-Time Emission Monitoring	Develop AI systems that provide real-time monitoring and reporting of vehicle emissions. These systems can enable immediate corrective actions and help regulatory agencies enforce emission standards effectively.
Predictive Emission Control	Implement AI algorithms that predict emissions based on driving conditions, enabling proactive emission reduction strategies. This can include adaptive engine control and route optimization.
Enhanced Fleet Management	Expand AI-powered fleet management solutions to optimize the operation of large vehicle fleets, including route planning, load balancing, and eco-driving coaching for commercial vehicles.

Table 9. *Cont.*

Direction	Description
Autonomous Vehicles and Emission Reduction	Advance the use of AI in autonomous vehicles to optimize driving patterns, minimize idle, and enhance communication between vehicles and traffic management systems for emission reduction.
Electric Vehicle Range Optimization	Develop AI systems that improve electric vehicle range predictions, taking into account factors such as weather, terrain, and driving habits. This can reduce "range anxiety" and promote electric vehicle adoption.
Integrated Transportation Ecosystem	Create AI-driven platforms that integrate various modes of transportation (e.g., public transit, ridesharing, electric scooters) to provide seamless, efficient, and eco-friendly travel options.
Emission Reduction Incentives	Utilize AI to design incentive programs for eco-friendly driving, such as discounted tolls or insurance rates for low-emission vehicles and eco-driving practices.
Air Quality Monitoring and Alerts	Enhance AI-powered air quality monitoring systems in urban areas and provide real-time alerts and recommendations to residents and policymakers.
Green Infrastructure Planning	Utilize AI for urban planning and infrastructure development, considering the impact on vehicle emissions. This can include optimizing traffic flow, promoting public transportation, and expanding electric vehicle charging networks.
Emission Reduction Regulation Compliance	Continue developing AI tools for robust emission testing and compliance verification, ensuring that vehicles meet stringent environmental standards and regulations.
Energy-Efficient Manufacturing	Apply AI in the manufacturing process to reduce the carbon footprint of vehicle production. AI can optimize supply chains, minimize waste, and improve energy efficiency.
Lifecycle Carbon Footprint Analysis	Develop comprehensive AI models that consider the environmental impact of a vehicle's entire lifecycle, from manufacturing and operation to disposal, helping consumers make informed decisions.
Public Awareness and Education	Utilize AI for personalized public awareness campaigns and eco-driving education, helping individuals understand their role in reducing emissions.
Global Collaboration and Standards	Foster international collaboration to establish global AI standards and best practices for vehicle emissions reduction, allowing consistency in technology implementation.

Source: Authors' own work based on: [110,113,114,116–119,121,124–127].

4.3. Smart Grid

Artificial intelligence is a very useful solution in enhancing the efficiency, reliability, and sustainability of smart grids, which are modernized electrical grids that use digital technology to monitor and manage electricity generation, distribution, and consumption. AI is applied in various ways within smart grids to optimize operations, improve energy management, and enhance overall grid performance [128].

The utilization of AI in the smart grid offers a digital framework that harnesses advanced technological capabilities. AI strategies within the smart grid encompass various aspects such as power management, automation of the power system, analysis of energy usage trends, and the detection of faults [129]. The ultimate objective of an intelligent grid is to substitute manual procedures with AI-driven solutions, resulting in enhanced efficiency, stability, and cost savings [130]. This covers every facet of an electrical network [128] including power generation [131], energy transmission [132], power conversion [133], electricity distribution [134], and energy consumption [135].

AI can analyze data from sensors and other sources to predict when grid equipment, such as transformers or circuit breakers, might fail. This proactive approach to maintenance reduces downtime and prevents costly outages [136]. AI can forecast electricity demand and adapt the grid's operation accordingly. It can communicate with smart appliances, thermostats, and electric vehicles to optimize energy consumption during periods of high demand or low supply [137], reducing peak load and managing grid stress [138].

Omitaomu and Niu [139] have described main artificial intelligence techniques which can be used in smart grids. The first important method is load forecasting. The increasing complexity of load forecasting is due to the integration of renewable energy sources in smart grids. Load forecasting is categorized into three levels: short-term load forecasting (STLF), mid-term load forecasting (MTLF), and long-term load forecasting (LTLF). Various

AI techniques, including deep learning, are explored to enhance forecasting accuracy. Another area where AI techniques can be useful is power grid stability assessment. Power grid stability, comprising transient stability, frequency stability, small-signal stability, and voltage stability are crucial to ensure the reliability and security of the power system. Traditional stability assessment models are complex and computationally intensive. Data-driven AI methods are useful for stability analysis, leveraging technologies such as phasor measurement units (PMUs) and wide area measurement systems (WAMSs).

Another potential of AI in smart grids is the usage of AI methods for fault detection in power systems. Various techniques, such as extreme learning machines (ELMs), support vector machines (SVMs), and ensemble models, are employed to detect and locate faults in power grids, including high-impedance faults in micro grids and line trip faults [140].

The AI can also be useful in the case of smart grid security. AI technologies, such as artificial neural networks (ANNs), support vector machines (SVMs), and reinforcement learning (RL), are employed to enhance smart grid security by detecting and preventing cyberattacks [128,141].

AI systems continuously monitor the grid for abnormal conditions or disturbances [142]. They can quickly identify and respond to issues such as power outages [142], equipment failures [143], or cybersecurity threats [128]. Its use can help in integrating variable energy sources like solar and wind into the grid by predicting their output based on weather conditions and adjusting grid operations to accommodate fluctuations in generation [144,145].

There are many key directions for the future usage of artificial intelligence in smart grids. The authors present them in Table 10.

Table 10. Key directions for future usage of AI in smart grids.

Direction	Description
Integration with Cloud Computing	To realize the vision of a fully self-learning smart grid, integrating AI with cloud computing is pivotal. This integration brings several benefits including increased security and robustness, and a reduction in downtime due to outages. The cloud acts as a reservoir of data and computational power, allowing smart grids to process information efficiently, adapt quickly to changing conditions, and make well-informed decisions.
Fog Computing	Fog computing introduces a paradigm shift by processing raw data locally, rather than transmitting it to distant cloud servers. This approach offers several advantages such as energy efficiency, scalability, and flexibility. Using on-demand computing resources, fog computing aligns perfectly with the demands of a modern smart grid. Preliminary research indicates its potential role in enhancing the reliability and performance of smart grids, particularly as the volume of data generated in these systems continues to escalate.
Transfer Learning	Smart grid analysis faces a persistent challenge: the scarcity of labeled data. To overcome this obstacle, researchers are turning to transfer learning, a technique that reduces the reliance on large volumes of training data. Recent years have witnessed a surge in interest in deep transfer learning tasks. These approaches hold great promise and could have widespread applications within smart grid systems, enabling them to adapt and learn even with limited data.
Consumer Behavior Prediction	In the era of fog computing and the evolution of 5G networks, predicting consumer behavior has become a critical task in managing power systems. Understanding and learning the patterns of consumer power consumption can significantly contribute to demand-side management. With the assistance of AI, smart grids can anticipate and respond to changes in energy consumption patterns, promoting efficient demand response initiatives.

Source: The authors' own work on the basis of: [99,128–130,132,134,135,137–139,141–157].

According to Seyd and Bong [128], AI techniques have revolutionized the energy market by providing efficient solutions for real-time demand response and decision-making. This enables grid operators to optimize all aspects of the power grid, from relay switching to large generator controls, and mitigate unwanted harmonics through sensor networks.

Those techniques play a crucial role in coordinating distributed energy resources, enhancing the acceptability of renewable energy sources, and increasing grid reliability. It allows for the efficient management of distributed generation and storage capacity, automatic regulation and optimization, bidirectional energy flow, and the integration of plug-in hybrid electric vehicles.

Distributed grid management requires real-time optimization for large-scale systems with renewable generators and controllable loads. AI techniques, such as consensus-based distributed computational intelligence, offer solutions to address the challenges of rapidly changing conditions, computation, and communication bottlenecks [148]. AI has driven the development of decentralized and intelligent controllers, improving processing speed, reliability, and efficacy. These controllers distribute operations among distributed units, reducing the burden on centralized controllers and improving the resilience of the system [158].

The traditional approach of using supervisory control and data acquisition (SCADA) systems has become impractical due to the complexity of modern grids. AI-driven distributed load balancing algorithms have emerged as effective solutions to optimize loads in distributed systems. AI and blockchain technologies have played a significant role in enhancing security and data management in smart grids, particularly in the context of distributed data storage and local energy trading [146].

According Sulaiman et al. [138], the integration of artificial intelligence into the smart grid presents significant opportunities and challenges. AI can enhance grid security by continuously monitoring, analyzing, and predicting potential threats and vulnerabilities. It enables proactive responses to security incidents, automates decision-making, and promotes collaboration among various infrastructure components in a smart city. However, there are several challenges that need to be addressed.

According to Zambrano and Giraldo [154], predictive models based on AI for renewable energy hold the promise of revealing valuable glimpses into the expected energy enhancements in the near future. Ruhnau et al. [155] believe that combining various approaches can refine these forecasts by making the most of the disparities in individual prediction models. These approaches encompass both standalone and integrated technologies that generate predictions based on distinct time series data derived from specific sources such as weather stations, wind turbines, or solar panels [109]. To enhance forecast precision, the incorporation of information from nearby areas to the location of interest has become increasingly popular, particularly in recent years [116].

In Table 11, there is a comparison of the advantages and disadvantages of AI usage in smart grids.

Table 11. Advantages and disadvantages of AI usage in smart grids.

Advantages	**Disadvantages**
Improved Grid Efficiency AI can optimize energy distribution and reduce energy waste, leading to improved grid efficiency.	Data Security Concerns AI systems may be susceptible to cyberattacks, potentially compromising the security and privacy of grid data and operations.
Enhanced Reliability AI enables predictive maintenance and self-healing capabilities, reducing downtime and improving grid reliability.	Initial Implementation Costs Integrating AI into smart grids can require substantial investments in infrastructure, technology, and expertise.
Real-time Monitoring AI allows for real-time monitoring and analysis of grid performance, enabling quick responses to fluctuations and outages.	Complexity and Maintenance AI systems can be complex to implement and maintain, requiring skilled personnel and ongoing updates.
Demand Response AI can predict and respond to changes in energy demand, facilitating efficient demand-side management.	Resource Intensive: AI systems may demand significant computational resources, potentially increasing operational costs.

Table 11. *Cont.*

Advantages	Disadvantages
Renewable Integration AI aids in the integration of renewable energy sources by optimizing their output and storage.	Data Privacy Concerns The collection and analysis of large amounts of data can raise concerns about consumer data privacy.
Grid Resilience AI can adapt to unexpected events and disasters, contributing to grid resilience and disaster recovery.	Algorithm Bias AI algorithms can exhibit bias based on the training data, potentially leading to unfair or inequitable outcomes.
Reduced Environmental Impact AI can minimize environmental impact by optimizing energy usage and promoting sustainable practices.	Lack of Human Oversight Excessive reliance on AI may reduce human oversight and decision-making, potentially introducing risks.

Source: The authors' own work based on: [88,92,99,104,128–130,132,134,135,137,139,142–145,148–160].

AI has enabled the emergence of "prosumers", allowing domestic energy users to both produce and consume electricity and share it with others. This shift from centralized, fossil-fueled generation to a decentralized, intelligent system enhances economic benefits for consumers, fostering energy sharing and trade [160].

Sami [153] described how to use AI in prosumers management. He pointed out that machine learning within the realm of artificial intelligence has the capability to assess and anticipate energy demand patterns and categorize irregular energy usage. By leveraging data collected through smart meters and subjecting it to AI analysis and data mining, it becomes feasible to discern various customer segments' electricity consumption behaviors. Subsequently, this data can be employed to enhance statistical precision, facilitating the targeted delivery of advertisements and services. Fluctuations in the environment, such as variations in weather conditions, alterations in electrical appliance usage, and changes in consumer behavior, can impact the accuracy of anomaly detection results. Consequently, it is imperative to emphasize potential adverse aspects within the power grid that could influence the equitable distribution of power among consumers. The analysis of energy consumption is intrinsically linked to human characteristics, which can be addressed by extracting or taxonomy features. In this context, the development of deep learning models, particularly multilayered hidden neural networks, augments the predictive performance of energy demand and consumption.

Rodgers et al. [147], in his study, underscores the significance of AI in smart grids, aligning goals with global sustainability objectives, emphasizing the role of ICT, and outlining practical requirements for smart grids. The study delves into the decision-making processes of experts and their knowledge transfer apparatus. It highlights the importance of information and communication technology (ICT) and AI usage in facilitating knowledge transfer for a greener environment. The authors have identified three key goals for smart grids: universal access to electricity, environmental protection, and efficiency. These goals align with global sustainability objectives, such as those set by the United Nations Conference on Sustainable Development (Rio + 20). The AI-based solutions can be useful to realize them.

The AI can be also used to enable smart grid stability prediction. This possible usage was described by Ucar [161]. He proposes an enhanced model using explainable AI and feature engineering for predicting the stability of the smart grid (SG). This model approaches the problem with both classification and regression, offering a holistic perspective on existing studies and proposing a novel structure to address their limitations. The GBM (gradient boosting machine) and deep learning models are introduced as effective tools for prediction, despite their drawbacks. The flexibility and practicality of GBMs make them valuable tools for model design and customization. The text concludes by emphasizing the importance of combining data analytics with smart grid research for future studies.

Summing up, artificial intelligence plays a pivotal role in optimizing the performance of smart grids by efficiently managing various grid operations and energy consumption. These AI-driven systems utilize load-forecasting techniques and predictive analysis to enhance stability, minimize downtime, and proactively maintain grid equipment, preventing costly outages. Moreover, AI facilitates real-time adjustments in energy consumption by communicating with smart appliances and electric vehicles, ensuring optimization during peak demand periods, and consequently reducing stress on the grid. AI's integration within the energy market enables grid operators to coordinate distributed energy resources efficiently, enhancing grid reliability and managing distributed generation and storage capacity effectively. Furthermore, AI-driven decentralized controllers enhance system resilience and processing speed, optimizing operations among distributed units, and reducing the dependency on centralized controllers. Moreover, AI's role extends to improving grid security by continuously monitoring and predicting potential threats, automating decision-making, and fostering collaboration among infrastructure components in smart cities.

4.4. Energy Storages

With the global shift toward renewable energy sources like solar and wind, the need for efficient and reliable energy storage solutions has become increasingly critical. AI plays an important role in addressing the challenges associated with energy storage, making it smarter, more cost-effective, and environmentally friendly [162].

Energy storage technology has a role to play in enhancing the capabilities for utilizing new energy sources, ensuring the reliable and cost-effective power systems operation, and advancing the extensive adoption of renewable energy technologies [163]. Various fresh innovations, concepts, methodologies, and technologies have been introduced in this domain, stemming from disciplines such as materials science, knowledge management, electrical engineering, control systems, and artificial intelligence [164].

AI algorithms are being used to enhance the performance of energy storage systems, particularly lithium-ion batteries. By continuously monitoring and analyzing data from these batteries, AI can optimize their charging and discharging cycles, extending their lifespan and improving their efficiency [133]. This not only reduces maintenance costs, but also reduces the environmental impact of battery disposal. This solution is employed to predict potential issues in energy storage systems before they lead to costly breakdowns [165]. Through real-time data analysis and machine learning models, AI can detect anomalies in system behavior, enabling operators to perform timely maintenance and prevent unexpected downtime [166].

Energy storage systems equipped with AI can respond rapidly to fluctuations in the grid. When the supply of renewable energy is inconsistent, AI can instantly adjust the flow of stored energy, stabilizing the grid and ensuring a consistent power supply [167].

In the literature, many techniques of AI usage in energy storage can be found. Ahmed and Abdallia [168] proposed hybrid differential evolution optimization of AI. The efficiency of the proposed controller is confirmed in an electrical grid that includes a synchronous generator, a photovoltaic power source, and a battery energy storage system. The controller's parameters are adaptively tuned in real-time by training the artificial neural network (ANN) with datasets generated during the optimization phase of both controllers using the hybrid differential evolution optimization method under varying levels of disturbance, ranging from low to high. Athari and Ardehali [169] used the fuzzy logic controller-based approach. The membership features of the fuzzy logic controller (FLC) are tailored to reduce operational costs in green energy hybrid systems. This reduction is achieved by utilizing weekly and periodic data predictions for factors such as water availability, electricity demand, and environmental conditions like wind speed, sunlight, and air temperature. This optimization process employs algorithms inspired by frog-spring shuffling. It is worth noting that accurate accounting of power grid costs plays a significant role in enhancing the efficiency of energy storage components for the hybrid renewable energy systems (HRESs) when connected to the grid. This efficiency improvement is achieved because the configured weekly and periodic FLCs help minimize the operating hours of fuel cells and gas-based generators while reducing state-of-charge (SOC) variability in the battery stack [168].

Zahedi and Ardehali [170] described the situation when a novel energy storage system (ESS) control system employing a multi-agent setup was implemented for a 100-megawatt system. The system's control performance was verified through simulation analysis and practical testing. The AI-driven solution based on hierarchical control was described by Yunhao et al. [171]. By employing balance regulation, the simulated impedance is dynamically adjusted to eliminate the impact of inaccurate line impedance on the precision of the current distribution. Subsequently, each power storage unit can fine-tune its current based on state-of-charge (SoC) balance control, taking into account its capacity and charging status. This helps reduce SoC discrepancies and facilitates a gradual state of charge (SoC) balance during both charging and discharging operations.

Summing up, artificial intelligence is revolutionizing energy storage solutions by optimizing the performance and longevity of storage systems. In energy storage, AI algorithms continuously analyze and fine-tune the charging and discharging cycles, notably enhancing the efficiency of lithium-ion batteries. By leveraging real-time data and predictive analytics, AI predicts potential system issues, enabling proactive maintenance, reducing downtime, and mitigating the environmental impact associated with battery disposal. These AI-driven solutions in energy storage effectively stabilize the grid by swiftly responding to fluctuations in renewable energy supply, ensuring consistent power flow and minimizing interruptions. Additionally, diverse AI-based approaches, such as hybrid optimization and fuzzy logic controllers, significantly improve system efficiency and reduce operational costs in hybrid renewable energy systems. These advancements underscore AI's role in enhancing the reliability, efficiency, and sustainability of energy storage systems, offering promising avenues for smarter and more eco-friendly energy management.

In Table 12, there is a comparison of the advantages and disadvantages of AI usage in energy storage management.

Table 12. Key directions for future usage of AI in energy storages.

Direction	Description
Optimized Energy Management	Implement AI to optimize the management of energy storage systems, maximizing their efficiency and overall performance.
Grid Integration	Develop AI solutions that facilitate seamless integration of energy storage with power grids, enhancing grid stability and ensuring reliable power supply.
Advanced Battery Technologies	Utilize AI to advance the development of new battery technologies, making them more efficient, longer lasting, and cost-effective.
Predictive Maintenance	Employ AI for predictive maintenance of energy storage systems to reduce downtime and extend the lifespan of storage devices.
Renewable Energy Synergy	Enhance AI algorithms to seamlessly integrate energy storage with renewable energy sources such as solar and wind, enabling more efficient and stable renewable energy utilization.
Decentralized Storage	Develop AI-driven solutions for managing decentralized energy storage resources, including microgrids and distributed storage systems, improving grid resilience.
Cybersecurity and Data Privacy	Strengthen cybersecurity measures to protect energy storage systems and ensure data privacy when handling sensitive grid information through AI technologies.
Energy Consumption Optimization	Use AI to optimize energy consumption patterns in homes, businesses, and industries, ensuring efficient use of stored energy and reducing energy waste.
Environmental Sustainability	Develop AI-powered solutions that promote environmental sustainability by minimizing the environmental impact of energy storage systems.
Regulatory Compliance	Collaborate with policymakers to ensure that AI-based energy storage systems comply with regulations and standards while promoting responsible and ethical AI use in the energy sector.

Source: Authors' own work on basis: [133,157,163,164,167,168,171–173].

5. Discussion–Challenges

Based on a review of the literature and an analysis of solutions based on artificial intelligence and connected to energy both at home and in cities, the authors identified and described the challenges in the given areas. This section is divided into two subsections corresponding to fields from Sections 3 and 4, and in each of these fields the authors have identified the most important challenges that resulted from a review of the latest research on the topic.

5.1. Field of Residential and Individual Users

In the first field, the following challenges were identified:

- Providing the desired level of resident comfort while minimizing energy consumption in smart homes;
- Providing cooperation of different devices in smart homes as they are often produced by different manufacturers and use various communication protocols;
- Ensuring that energy management systems in homes effectively reduce energy consumption and not inadvertently increase it through constant connectivity and device usage;
- Using machine learning and deep reinforcement learning to manage appliances, distributed energy sources, and electric vehicle charging in smart homes;
- Providing the stability and availability of energy sources for smart homes as smart homes become more dependent on renewable energy sources;
- Coordinating energy consumption in smart homes with the growing adoption of renewable energy sources;
- Optimizing AI-driven HVAC systems by making real-time adjustments based on data from sources such as weather forecasts and occupancy patterns;
- Developing AI-driven home energy management systems that adapt to changes in electricity prices and consumption;
- Providing the compatibility of smart lighting with various smart home platforms;
- Developing cost-effective and environmentally sustainable lighting systems;
- Developing and implementing new materials in smart windows to control natural light and use it to obtain the optimal temperature inside building;
- Creating intelligent control systems for smart blinds that adapt to changing sunlight and temperature to ensure optimal light management and energy efficiency in homes;
- Designing hardware upgrades for refrigerators to improve efficiency while ensuring food safety;
- Developing self-learning smart thermostats for more extensive applications;
- Getting users to adopt energy-efficient behaviors and make the most of smart home features is vital—educating and motivating users is vital.

5.2. Field of Urban Infrastructure

In the other field, the following challenges were identified:

- Implementing of AI in the charging infrastructure can come with high upfront costs for hardware, software, and integration;
- Dependency of the charging infrastructure on AI systems, which can occasionally experience downtime or errors, potentially inconveniencing EV owners;
- Collecting of user data and behavior monitoring for optimal charging can raise privacy concerns, necessitating robust data protection measures;
- Shifting to AI-powered charging infrastructure may lead to traditional charging station maintenance jobs being displaced;
- Protecting the charging infrastructure from hacking and fraud is a significant concern, requiring strong cybersecurity measures;
- Requirements of AI systems ongoing updates and maintenance to ensure their effectiveness and security;
- Resistance of some users to adopt AI technology to charge their EVs;
- Integrating AI into existing infrastructure and grid systems can be complex and require standardization;
- Implementing AI solutions for vehicle emission reduction may involve integration costs and technology adoption challenges;

- Ensuring that vehicles meet stringent emission standards and regulations requires the development of robust AI tools;
- Convincing drivers to adopt eco-friendly driving practices may be a challenge;
- Fostering international collaboration and standards for AI in vehicle emission reduction can be complex;
- Using of AI in smart grids and energy storage systems introduces cybersecurity risks, potentially compromising the security and privacy of grid data and operations;
- Integrating AI into smart grids and energy storage systems can require substantial investments in infrastructure, technology, and expertise;
- Implementation complexity and maintenance of AI-driven systems, requiring skilled personnel and ongoing updates to keep them operational;
- Requiring substantial computational resources, AI systems could potentially escalate operational expenses;
- AI algorithms have the potential to display bias linked to the training data, potentially resulting in outcomes that are unfair or inequitable;
- Depending excessively on AI could potentially diminish human oversight and decision-making, introducing possible risks;
- The gathering and analyzing of extensive data could potentially cause concerns about the privacy of consumer data.

5.3. Scenarios

Overcoming these challenges will be essential for the successful integration of smart homes and smart cities and efficient usage of energy in the future. It will require a collaborative effort from manufacturers, policymakers, and consumers.

Summing up the challenges, the following scenarios for future usage of AI within energy can be considered:

- AI-driven smart home adaptability: creating adaptive AI systems that learn user behaviors and preferences to optimize energy usage in smart homes. These systems should harmonize various devices, predict consumption patterns, and adjust settings in response to changing conditions, ensuring energy efficiency without compromising user comfort.
- Secure and privacy-enhanced charging infrastructure: development of AI-powered charging stations equipped with robust cybersecurity measures and privacy protocols. These systems ensure seamless operation, user data protection, and effective energy management, overcoming privacy concerns and fostering greater EV adoption.
- Standardized integration of AI in urban grids: establishing standardized protocols for integrating AI into urban grids and infrastructure. This involves collaborative efforts to ensure the compatibility, cybersecurity, and seamless integration of AI solutions across various urban energy systems, ensuring reliable and efficient energy distribution.
- Emission reduction through AI-optimized driving: implementing AI-based systems that actively encourage eco-friendly driving behaviors. These systems utilize real-time data analysis, offering personalized feedback and incentives to drivers, promoting fuel-efficient driving habits and reducing vehicle emissions.
- Fairness and bias mitigation in AI algorithms: addressing biases in AI algorithms used for energy management by implementing fairness-aware and transparent AI models. Efforts should focus on developing tools that detect and mitigate biases, ensuring equitable outcomes and fair decision-making in energy-related AI applications.
- Collaborative international AI standards: facilitating international collaboration to establish unified AI standards for energy solutions. This involves harmonizing regulations, sharing best practices, and fostering a global framework that promotes ethical use of AI in managing energy systems.

These scenarios represent potential directions for the use of AI in energy-related domains, offering solutions to overcome existing challenges while emphasizing collaboration among stakeholders, policymakers, manufacturers, and consumers to ensure sustainable and efficient energy usage in the future.

6. Conclusions

The paper presents a comprehensive review of AI-driven solutions in the urban energy sector, shedding light on the significant impacts and promising applications of artificial intelligence. Through a literature review including papers from 2019 to 2023, the study categorizes these solutions into two main areas: residential and individual user applications, and urban infrastructure integration for both individual users and communities. The review has achieved its objectives, as follows:

- O1: to identify trends, emerging technologies, and applications using artificial intelligence in the energy field:
  - The examination has shown key emerging technologies in AI-driven energy solutions for residential users and society at large. They include solutions for individual users in homes, such as AI-driven heating and cooling, lighting, windows and blinds, home devices—refrigerators, and energy management systems. When it comes to society, the following are most popular: electric vehicle charging infrastructure, vehicle emission reduction, smart grid, and energy storages.
- O2: to provide up-to-date insights into the use of artificial intelligence in energy-related applications:
  - Focusing on recent research, the paper has provided valuable insights into the current state of AI-driven urban energy solutions. It highlights the rapid evolution of technology and its growing role in shaping urban energy systems.
- O3: to gain a comprehensive understanding of the current state of AI-driven urban energy solutions:
  - The review has deepened our understanding of the dynamic field of AI-driven urban energy solutions. It elucidates how AI is being integrated into various aspects of urban living, from individual homes to a broader community infrastructure.
- O4: to explore future directions, emerging trends, and challenges in the field of AI-driven energy solutions:
  - The paper acknowledges the transformative potential of AI in urban energy management while recognizing the challenges ahead. It shows the way for future research activities by offering a view of AI-driven solutions in homes and cities.

The research questions have been addressed with meaningful insights:

- R1: What are the key emerging technologies in AI-driven energy solutions for residential users and society?
  - The paper identifies emerging technologies that are set to transform the energy landscape, including smart home devices, electric vehicle infrastructure, smart grids, and more. These technologies promise to improve energy efficiency, reduce carbon emissions, and enhance the quality of life of urban residents.
- R2: How is artificial intelligence integrated into urban infrastructure to enhance energy-related solutions?
  - Artificial intelligence is integrating into urban infrastructure to optimize energy-related solutions. This includes the enhancement of electric vehicle charging infrastructure, reduction in vehicle emissions, development of smart grids, and efficient energy storage.
- R3: What challenges are associated with the implementation of AI-driven solutions in urban energy management?
  - The challenges include the need to balance resident comfort with energy efficiency in smart homes, ensuring compatibility and cooperation among various devices, and preventing unintended energy consumption increases due to con-

stant connectivity. The challenges also extend to managing renewable energy sources, coordinating energy consumption, and optimizing HVAC systems in smart homes. In the field of urban infrastructure, challenges involve high upfront costs, privacy concerns about user data, potential job displacement, cybersecurity risks, technology adoption, and others.

In conclusion, this paper serves as a valuable resource for researchers, policymakers, and practitioners in the field of urban energy management. Researchers should focus on interdisciplinary collaborations, exploring AI's depth in urban energy management. Policymakers could help by incentivizing AI integration and establishing standards, while practitioners should focus on real-world trials and user-centric AI implementations. This paper not only highlights the transformative potential of AI but also underscores the need for a collaborative effort to overcome challenges and harness the full benefits of artificial intelligence in creating smarter, more sustainable, and energy-efficient urban environments.

The biggest limitation of this study is the lack of a detailed analysis of individual solutions based on artificial intelligence, although this is due to the huge number of these solutions. While the article reviews these solutions broadly, it refrains from delving into specific details and intricacies due to the overwhelming volume and scope of the discussed solutions.

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References

1. Ranosz, R.; Bluszcz, A.; Kowal, D. Conditions for the innovation activities of energy sector enterprises shown on the example of mining companies. *Inżynieria Miner.* **2020**, *1*, 249–256. [CrossRef]
2. Bluszcz, A.; Manowska, A. Differentiation of the level of sustainable development of energy markets in the European Union countries. *Energies* **2020**, *13*, 4882. [CrossRef]
3. Jelonek, D.; Chomiak-Orsa, I. The Application of ICT in the Area of Value Co-Creation Mechanisms Support as a Determinant of Innovation Activities. *Int. J. Ambient Comput. Intell.* **2018**, *9*, 32–42. [CrossRef]
4. Sadeeq, M.M.; Abdulkareem, N.M.; Zeebaree, S.R.M.; Ahmed, D.M.; Sami, A.S.; Zebari, R.R. IoT and Cloud computing issues, challenges and opportunities: A review. *Qubahan Acad. J.* **2021**, *1*, 1–7. [CrossRef]
5. Awan, F.M.; Minerva, R.; Crespi, N. Using Noise Pollution Data for Traffic Prediction in Smart Cities: Experiments Based on LSTM Recurrent Neural Networks. *IEEE Sens. J.* **2021**, *21*, 20722–20729. [CrossRef]
6. Koval, V.; Borodina, O.; Lomachynska, I.; Olczak, P.; Mumladze, A.; Matuszewska, D. Model Analysis of Eco-Innovation for National Decarbonisation Transition in Integrated European Energy System. *Energies* **2022**, *15*, 3306. [CrossRef]
7. Kulpa, J.; Kamiński, P.; Stecuła, K.; Prostański, D.; Matusiak, P.; Kowol, D.; Kopacz, M.; Olczak, P. Technical and Economic Aspects of Electric Energy Storage in a Mine Shaft—Budryk Case Study. *Energies* **2021**, *14*, 7337. [CrossRef]
8. Stecuła, K.; Olczak, P.; Kamiński, P.; Matuszewska, D.; Duong Duc, H. Towards Sustainable Transport: Techno-Economic Analysis of Investing in Hydrogen Buses in Public Transport in the Selected City of Poland. *Energies* **2022**, *15*, 9456. [CrossRef]
9. Kinelski, G. Smart-city trends in the environment of sustainability as support for decarbonization processes. *Polityka Energetyczna* **2022**, *25*, 109–136. [CrossRef]
10. Sribna, Y.; Koval, V.; Olczak, P.; Bizonych, D.; Matuszewska, D.; Shtyrov, O. Forecasting solar generation in energy systems to accelerate the implementation of sustainable economic development. *Polityka Energetyczna* **2021**, *24*, 5–28. [CrossRef]
11. Jia, L.; Cheng, P.; Yu, Y.; Chen, S.; Wang, C.; He, L.; Nie, H.; Wang, J.; Zhang, J.; Fan, B.; et al. Regeneration mechanism of a novel high-performance biochar mercury adsorbent directionally modified by multimetal multilayer loading. *J. Environ. Manag.* **2023**, *326*, 116790. [CrossRef]
12. Salehi-Amiri, A.; Akbapour, N.; Hajiaghaei-Keshteli, M.; Gajpal, Y.; Jabbarzadeh, A. Designing an effective two-stage, sustainable, and IoT based waste management system. *Renew. Sustain. Energy Rev.* **2022**, *157*, 112031. [CrossRef]

13. Anastasi, G.; Bartoli, C.; Conti, P.; Crisostomi, E.; Franco, A.; Saponara, S.; Testi, D.; Thomopulos, D.; Vallati, C. Optimized energy and air quality management of shared smart buildings in the COVID-19 scenario. *Energies* **2021**, *14*, 2124. [CrossRef]
14. Loska, A.; Paszkowski, W. Smartmaintenance—The concept of supporting the exploitation decision-making process in the selected technical network system. *Adv. Intell. Syst. Comput.* **2018**, *637*, 64–73. [CrossRef]
15. Chomiak-Orsa, I.; Domagała, P.; Greńczuk, A.; Grzelak, W.; Hauke, K.; Kotwica, A.; Perechuda, K.; Pondel, M. Open Data for simulation to determine the efficient management of parking spaces in Smart City. *Procedia Comput. Sci.* **2022**, *207*, 3625–3634. [CrossRef]
16. Paszkowski, W.; Loska, A. The use of neural network model in the assessment of annoyance of the industrial noise sources. In *International Conference on Intelligent Systems in Production Engineering and Maintenance*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 428–439.
17. Stecuła, K. Virtual Reality Applications Market Analysis—On the Example of Steam Digital Platform. *Informatics* **2022**, *9*, 100. [CrossRef]
18. Zhang, C.; Lu, Y. Study on artificial intelligence: The state of the art and future prospects. *J. Ind. Inf. Integr.* **2021**, *23*, 100224. [CrossRef]
19. Bluszcz, A.; Tobór-Osadnik, K.; Tomiczek, K.; Mansora, N.S.; Awang, H. The Use of Geomatics Tools in Critical Infrastructure Management. *Inżynieria Miner.* **2023**, *1*, 169–174. [CrossRef]
20. Bluszcz, A.; Manowska, A. The use of hierarchical agglomeration methods in assessing the Polish energy market. *Energies* **2021**, *14*, 3958. [CrossRef]
21. Morse, H.F.; AlGhamdi, M.S.; Almusaied, H.M.; Alsubaie, S.A.; Almarri, D.M.; Alqahtani, M.A.; Alqahtani, R.A.; Tabeidi, R.A.; Balharith, T. The Smart Heater Based on Internet of Things. In *The International Conference on Artificial Intelligence and Computer Vision*; Springer: Berlin/Heidelberg, Germany, 2021; Volume 1377, pp. 145–153.
22. Sadeghian Broujeny, R.; Madani, K.; Chebira, A.; Amarger, V.; Hurtard, L. A Heating Controller Designing Based on Living Space Heating Dynamic's Model Approach in a Smart Building. *Energies* **2021**, *14*, 998. [CrossRef]
23. Png, E.; Srinivasan, S.; Bekiroglu, K.; Chaoyang, J.; Su, R.; Poolla, K. An internet of things upgrade for smart and scalable heating, ventilation and air-conditioning control in commercial buildings. *Appl. Energy* **2019**, *239*, 408–424. [CrossRef]
24. Al Essa, M.J.M. Energy management of space-heating systems and grid-connected batteries in smart homes. *Energy Ecol. Environ.* **2022**, *7*, 1–14. [CrossRef]
25. Huchuk, B.; Sanner, S.; O'Brien, W. Development and evaluation of data-driven controls for residential smart thermostats. *Energy Build.* **2021**, *249*, 111201. [CrossRef]
26. Afram, A.; Janabi-Sharifi, F.; Fung, A.S.; Raahemifar, K. Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system. *Energy Build.* **2017**, *141*, 96–113. [CrossRef]
27. 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]
28. Claessens, B.J.; Vanhoudt, D.; Desmedt, J.; Ruelens, F. Model-free control of thermostatically controlled loads connected to a district heating network. *Energy Build.* **2018**, *159*, 1–10. [CrossRef]
29. Marantos, C.; Lamprakos, C.; Siozios, K.; Soudris, D. Towards Plug&Play smart thermostats for building's heating/cooling control. In *IoT for Smart Grids Design Challenges and Paradigms*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 183–207.
30. Goman, V.V.; Korolev, S.I. Smart thermostats in building automation systems and smart homes. *KnE Eng.* **2020**, *5*, 67–74. [CrossRef]
31. Huang, K.; Hallinan, K.P.; Lou, R.; Alanezi, A.; Alshatshati, S.; Sun, Q. Self-learning algorithm to predict indoor temperature and cooling demand from smart WiFi thermostat in a residential building. *Sustainability* **2020**, *12*, 7110. [CrossRef]
32. Duman, A.C.; Erden, H.S.; Gönül, Ö.; Güler, Ö. A home energy management system with an integrated smart thermostat for demand response in smart grids. *Sustain. Cities Soc.* **2021**, *65*, 102639. [CrossRef]
33. An, Y.; Fu, Y.; Dai, J.-G.; Yin, X.; Lei, D. Switchable radiative cooling technologies for smart thermal management. *Cell Rep. Phys. Sci.* **2022**, *3*, 101098. [CrossRef]
34. Daneshvar, Y.; Sabzehparvar, M.; Hashemi, S.A.H. Energy efficiency of small buildings with smart cooling system in the summer. *Front. Energy* **2020**, *16*, 651–660. [CrossRef]
35. Nezhad, A.E.; Rahimnejad, A.; Gadsden, S.A. Home energy management system for smart buildings with inverter-based air conditioning system. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107230. [CrossRef]
36. Hou, X.; Wang, J.; Huang, T.; Wang, T.; Wang, P. Smart home energy management optimization method considering energy storage and electric vehicle. *IEEE Access* **2019**, *7*, 144010–144020. [CrossRef]
37. Dong, B.; Shi, Q.; Yang, Y.; Wen, F.; Zhang, Z.; Lee, C. Technology evolution from self-powered sensors to AIoT enabled smart homes. *Nano Energy* **2021**, *79*, 105414. [CrossRef]
38. Alipio, M.; Bures, M. Intelligent Network Maintenance Modeling for Fixed Broadband Networks in Sustainable Smart Homes. *IEEE Internet Things J.* **2023**, *10*, 18067–18081. [CrossRef]
39. Garcia-Magarino, I.; Muttukrishnan, R.; Lloret, J. Human-centric AI for trustworthy IoT systems with explainable multilayer perceptrons. *IEEE Access* **2019**, *7*, 125562–125574. [CrossRef]

40. Ayan, O.; Turkay, B. IoT-based energy efficiency in smart homes by smart lighting solutions. In Proceedings of the 2020 21st International Symposium on Electrical Apparatus & Technologies (SIELA), Bourgas, Bulgaria, 3–6 June 2020; IEEE: Toulouse, France, 2020; pp. 1–5.
41. Li, Z.; Li, J.; Li, X.; Yang, Y.; Xiao, J.; Xu, B. Design of office intelligent lighting system based on Arduino. *Procedia Comput. Sci.* **2020**, *166*, 134–138. [CrossRef]
42. Chiesa, G.; Di Vita, D.; Ghadirzadeh, A.; Herrera, A.H.M.; Rodriguez, J.C.L. A fuzzy-logic IoT lighting and shading control system for smart buildings. *Autom. Constr.* **2020**, *120*, 103397. [CrossRef]
43. Andramuño, J.; Mendoza, E.; Núñez, J.; Liger, E. Intelligent distributed module for local control of lighting and electrical outlets in a home. *J. Phys. Conf. Ser.* **2021**, *1730*, 12001. [CrossRef]
44. Cho, Y.; Seo, J.; Lee, H.; Choi, S.; Choi, A.; Sung, M.; Hur, Y. Platform design for lifelog-based smart lighting control. *Build. Environ.* **2020**, *185*, 107267. [CrossRef]
45. Ozeer, U.; Letondeur, L.; Ottogalli, F.-G.; Salaün, G.; Vincent, J.-M. Designing and implementing resilient IoT applications in the fog: A smart home use case. In Proceedings of the 2019 22nd Conference on Innovation in Clouds, Internet and Networks and Workshops (ICIN), Paris, France, 19–21 February 2019; IEEE: Toulouse, France, 2019; pp. 230–232.
46. Khoa, T.A.; Nhu, L.M.B.; Son, H.H.; Trong, N.M.; Phuc, C.H.; Phuong, N.T.H.; Van Dung, N.; Nam, N.H.; Chau, D.S.T.; Duc, D.N.M. Designing efficient smart home management with IoT smart lighting: A case study. *Wirel. Commun. Mob. Comput.* **2020**, *2020*, 8896637. [CrossRef]
47. Touqeer, H.; Zaman, S.; Amin, R.; Hussain, M.; Al-Turjman, F.; Bilal, M. Smart home security: Challenges, issues and solutions at different IoT layers. *J. Supercomput.* **2021**, *77*, 14053–14089. [CrossRef]
48. Zhou, Y.; Fan, F.; Liu, Y.; Zhao, S.; Xu, Q.; Wang, S.; Luo, D.; Long, Y. Unconventional smart windows: Materials, structures and designs. *Nano Energy* **2021**, *90*, 106613. [CrossRef]
49. Cannavale, A.; Ayr, U.; Fiorito, F.; Martellotta, F. Smart electrochromic windows to enhance building energy efficiency and visual comfort. *Energies* **2020**, *13*, 1449. [CrossRef]
50. Ke, Y.; Chen, J.; Lin, G.; Wang, S.; Zhou, Y.; Yin, J.; Lee, P.S.; Long, Y. Smart windows: Electro-, thermo-, mechano-, photochromics, and beyond. *Adv. Energy Mater.* **2019**, *9*, 1902066. [CrossRef]
51. Wang, S.; Zhou, Y.; Jiang, T.; Yang, R.; Tan, G.; Long, Y. Thermochromic smart windows with highly regulated radiative cooling and solar transmission. *Nano Energy* **2021**, *89*, 106440. [CrossRef]
52. Zhang, S.; Cao, S.; Zhang, T.; Lee, J.Y. Plasmonic Oxygen-Deficient TiO_{2-x} Nanocrystals for Dual-Band Electrochromic Smart Windows with Efficient Energy Recycling. *Adv. Mater.* **2020**, *32*, 2004686. [CrossRef]
53. Li, G.; Chen, J.; Yan, Z.; Wang, S.; Ke, Y.; Luo, W.; Ma, H.; Guan, J.; Long, Y. Physical crosslinked hydrogel-derived smart windows: Anti-freezing and fast thermal responsive performance. *Mater. Horiz.* **2023**, *10*, 2004–2012. [CrossRef] [PubMed]
54. Zhou, Y.; Dong, X.; Mi, Y.; Fan, F.; Xu, Q.; Zhao, H.; Wang, S.; Long, Y. Hydrogel smart windows. *J. Mater. Chem. A* **2020**, *8*, 10007–10025. [CrossRef]
55. Zhou, Y.; Wang, S.; Peng, J.; Tan, Y.; Li, C.; Boey, F.Y.C.; Long, Y. Liquid thermo-responsive smart window derived from hydrogel. *Joule* **2020**, *4*, 2458–2474. [CrossRef]
56. Chen, L.; Duan, G.; Zhang, C.; Cheng, P.; Wang, Z. 3D printed hydrogel for soft thermo-responsive smart window. *Int. J. Extrem. Manuf.* **2022**, *4*, 25302. [CrossRef]
57. Aburas, M.; Soebarto, V.; Williamson, T.; Liang, R.; Ebendorff-Heidepriem, H.; Wu, Y. Thermochromic smart window technologies for building application: A review. *Appl. Energy* **2019**, *255*, 113522. [CrossRef]
58. Nundy, S.; Mesloub, A.; Alsolami, B.M.; Ghosh, A. Electrically actuated visible and near-infrared regulating switchable smart window for energy positive building: A review. *J. Clean. Prod.* **2021**, *301*, 126854. [CrossRef]
59. Tällberg, R.; Jelle, B.P.; Loonen, R.; Gao, T.; Hamdy, M. Comparison of the energy saving potential of adaptive and controllable smart windows: A state-of-the-art review and simulation studies of thermochromic, photochromic and electrochromic technologies. *Sol. Energy Mater. Sol. Cells* **2019**, *200*, 109828. [CrossRef]
60. Jung, W.; Hong, T.; Oh, J.; Kang, H.; Lee, M. Development of a prototype for multi-function smart window by integrating photovoltaic blinds and ventilation system. *Build. Environ.* **2019**, *149*, 366–378. [CrossRef]
61. Kang, H.; Hong, T.; Jung, S.; Lee, M. Techno-economic performance analysis of the smart solar photovoltaic blinds considering the photovoltaic panel type and the solar tracking method. *Energy Build.* **2019**, *193*, 1–14. [CrossRef]
62. Kang, H.; Hong, T.; Lee, M. Technical performance analysis of the smart solar photovoltaic blinds based on the solar tracking methods considering the climate factors. *Energy Build.* **2019**, *190*, 34–48. [CrossRef]
63. Wang, K.; Ti, Y.; Liu, D.; Chen, S. A Smart Refrigerator Architecture that Reduces Food Ingredients Waste Materials and Energy Consumption. *Ekoloji Derg.* **2019**, *107*, 4873–4878.
64. Phuchamniphatthananun, A.; Pora, W. A smart domestic refrigerator with energy efficiency improvement. In Proceedings of the 2019 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS), Bangkok, Thailand, 11–14 November 2019; IEEE: Toulouse, France, 2019; pp. 345–348.
65. Sabegh, M.R.Z.; Bingham, C.M. Impact of hysteresis control and internal thermal mass on the energy efficiency of IoT-controlled domestic refrigerators. In Proceedings of the 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), Oshawa, ON, Canada, 12–14 August 2019; IEEE: Toulouse, France, 2019; pp. 103–107.

66. Griva, A.I.; Rekkas, V.P.; Koritsoglou, K.; Sotiroudis, S.P.; Boursianis, A.D.; Papadopoulou, M.S.; Goudos, S.K. Energy Consumption Assessment in Refrigeration Equipment: The SmartFridge Project. In Proceedings of the 2023 12th International Conference on Modern Circuits and Systems Technologies (MOCAST), Athens, Greece, 28–30 June 2023; IEEE: Toulouse, France, 2023; pp. 1–4.
67. Pérez-Gomariz, M.; López-Gómez, A.; Cerdán-Cartagena, F. Artificial neural networks as artificial intelligence technique for energy saving in refrigeration systems—A review. *Clean Technol.* **2023**, *5*, 116–136. [CrossRef]
68. Cai, S. Research on Intelligent Refrigerator Control based on Artificial Intelligence Algorithm. *Highlights Sci. Eng. Technol.* **2023**, *35*, 12–16. [CrossRef]
69. Eltawil, M.A.; Mohammed, M.; Alqahtani, N.M. Developing Machine Learning-Based Intelligent Control System for Performance Optimization of Solar PV-Powered Refrigerators. *Sustainability* **2023**, *15*, 6911. [CrossRef]
70. Lu, R.; Hong, S.H.; Yu, M. Demand response for home energy management using reinforcement learning and artificial neural network. *IEEE Trans. Smart Grid* **2019**, *10*, 6629–6639. [CrossRef]
71. Majchrzak, K.; Olczak, P.; Matuszewska, D.; Wdowin, M. Economic and environmental assessment of the use of electric cars in Poland. *Polityka Energ.-Energy Policy J.* **2021**, *24*, 153–168. [CrossRef]
72. Markowska, K.; Sękala, A.; Stecuła, K.; Kawka, T.; Sirovitskiy, K.; Pankova, O.; Vnukova, N.; Shulyak, M.; Kharchenko, S.; Shchur, T. Comparison of the Sustainability and Economic Efficiency of an Electric Car and an Aircraft—A Case Study. *Sustainability* **2023**, *15*, 1238. [CrossRef]
73. Bazhinov, O.; Kravtson, M.; Bazhynova, T.; Haiek, Y.; Kharchenko, S.; Shchur, T.; Markowska, K.; Sękala, A.; Stecuła, K.; Kawka, T. Determination of the quality index of cars. *Sci. J. Silesian Univ. Technol. Ser. Transp.* **2023**, *118*, 17–28. [CrossRef]
74. Ma, Y.; Chen, X.; Wang, L.; Yang, J. Study on smart home energy management system based on artificial intelligence. *J. Sens.* **2021**, *2021*, 9101453. [CrossRef]
75. Chauhan, R.K.; Chauhan, K.; Badar, A.Q.H. Optimization of electrical energy waste in house using smart appliances management System-A case study. *J. Build. Eng.* **2022**, *46*, 103595. [CrossRef]
76. Olczak, P.; Żelazna, A.; Stecuła, K.; Matuszewska, D.; Lelek, Ł. Environmental and economic analyses of different size photovoltaic installation in Poland. *Energy Sustain. Dev.* **2022**, *70*, 160–169. [CrossRef]
77. Kulpa, J.; Olczak, P.; Stecuła, K.; Sołtysik, M. The Impact of RES Development in Poland on the Change of the Energy Generation Profile and Reduction of CO2 Emissions. *Appl. Sci.* **2022**, *12*, 11064. [CrossRef]
78. 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]
79. Rocha, H.R.O.; Honorato, I.H.; Fiorotti, R.; Celeste, W.C.; Silvestre, L.J.; Silva, J.A.L. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. *Appl. Energy* **2021**, *282*, 116145. [CrossRef]
80. Nutakki, M.; Mandava, S. Review on optimization techniques and role of Artificial Intelligence in home energy management systems. *Eng. Appl. Artif. Intell.* **2023**, *119*, 105721. [CrossRef]
81. Han, B.; Zahraoui, Y.; Mubin, M.; Mekhilef, S.; Seyedmahmoudian, M.; Stojcevski, A. Home Energy Management Systems: A Review of the Concept, Architecture, and Scheduling Strategies. *IEEE Access* **2023**, *11*, 19999–20025. [CrossRef]
82. Ajitha, A.; Radhika, S. A comprehensive review of demand response strategies and the role of emergent technologies for sustainable home energy management systems. *Int. J. Ambient Energy* **2023**, *44*, 2262–2282. [CrossRef]
83. 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]
84. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *J. Clean. Prod.* **2021**, *289*, 125834. [CrossRef]
85. Tushar, W.; Yuen, C.; Saha, T.K.; Morstyn, T.; Chapman, A.C.; Alam, M.J.E.; Hanif, S.; Poor, H.V. Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges. *Appl. Energy* **2021**, *282*, 116131. [CrossRef]
86. Li, J.; Herdem, M.S.; Nathwani, J.; Wen, J.Z. Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management. *Energy AI* **2023**, *11*, 100208. [CrossRef]
87. Sun, D.; Ou, Q.; Yao, X.; Gao, S.; Wang, Z.; Ma, W.; Li, W. Integrated human-machine intelligence for EV charging prediction in 5G smart grid. *EURASIP J. Wirel. Commun. Netw.* **2020**, *2020*, 139. [CrossRef]
88. Ahmed, M.; Zheng, Y.; Amine, A.; Fathiannasab, H.; Chen, Z. The role of artificial intelligence in the mass adoption of electric vehicles. *Joule* **2021**, *5*, 2296–2322. [CrossRef]
89. Raza, A.; Baloch, M.H.; Ali, I.; Ali, W.; Hassan, M.; Karim, A. Artificial Intelligence and IoT-Based Autonomous Hybrid Electric Vehicle with Self-Charging Infrastructure. In Proceedings of the 2022 International Conference on Emerging Technologies in Electronics, Computing and Communication (ICETECC), Jamshoro, Pakistan, 7–9 December 2022; IEEE: Toulouse, France, 2022; pp. 1–6.
90. Bajaj, D.K.; Siddharth, P. Artificial Intelligence (AI) in Electrical Vehicles. In *Recent Advances in Energy Harvesting Technologies*; River Publishers: Roma, Italy, 2023; pp. 57–76.
91. ElHusseini, H.; Assi, C.; Moussa, B.; Attallah, R.; Ghrayeb, A. Blockchain, AI and smart grids: The three musketeers to a decentralized EV charging infrastructure. *IEEE Internet Things Mag.* **2020**, *3*, 24–29. [CrossRef]
92. Paret, P.; Finegan, D.; Narumanchi, S. Artificial Intelligence for Power Electronics in Electric Vehicles: Challenges and Opportunities. *J. Electron. Packag.* **2023**, *145*, 34501. [CrossRef]

93. Swarnkar, R.; Harikrishnan, R.; Thakur, P.; Singh, G. Electric Vehicle Lithium-ion Battery Ageing Analysis Under Dynamic Condition: A Machine Learning Approach. *SAIEE Afr. Res. J.* **2022**, *114*, 4–13. [CrossRef]
94. Li, C.; Dong, Z.; Chen, G.; Zhou, B.; Zhang, J.; Yu, X. Data-driven planning of electric vehicle charging infrastructure: A case study of Sydney, Australia. *IEEE Trans. Smart Grid* **2021**, *12*, 3289–3304. [CrossRef]
95. Chen, Q.; Folly, K.A. Application of Artificial Intelligence for EV Charging and Discharging Scheduling and Dynamic Pricing: A Review. *Energies* **2022**, *16*, 146. [CrossRef]
96. Dharavat, N.; Golla, N.K.; Sudabattula, S.K.; Velamuri, S.; Kantipudi, M.V.V.; Kotb, H.; AboRas, K.M. Impact of plug-in electric vehicles on grid integration with distributed energy resources: A review. *Front. Energy Res.* **2023**, *10*, 1099890. [CrossRef]
97. Cao, Y.; Cui, J.; Liu, S.; Li, X.; Zhou, Q.; Hu, C.; Zhuang, Y.; Liu, Z. A Holistic Review on E-Mobility Service Optimization: Challenges, Recent Progress and Future Directions. *IEEE Trans. Transp. Electrif.* **2023**. [CrossRef]
98. Mosayebi, M.; Gheisarnejad, M.; Farsizadeh, H.; Andresen, B.; Khooban, M.H. Smart extreme fast portable charger for electric vehicles-based artificial intelligence. *IEEE Trans. Circuits Syst. II Express Briefs* **2022**, *70*, 586–590. [CrossRef]
99. Lazari, V.; Chassiakos, A. Multi-Objective Optimization of Electric Vehicle Charging Station Deployment Using Genetic Algorithms. *Appl. Sci.* **2023**, *13*, 4867. [CrossRef]
100. Rimal, B.P.; Kong, C.; Poudel, B.; Wang, Y.; Shahi, P. Smart electric vehicle charging in the era of internet of vehicles, emerging trends, and open issues. *Energies* **2022**, *15*, 1908. [CrossRef]
101. Herrlich, E.; Schaich, E.; Wagner, S.; Uckelmann, D. Parking and charging: New concepts for the use of intelligent charging infrastructure in car parks. In *iCity. Transformative Research for the Livable, Intelligent, and Sustainable City*; Springer: Cham, Switzerland, 2022; pp. 183–195.
102. Hu, S.; Mao, F.; Chen, J.; Li, Z. A review of charging infrastructure layout planning and electric vehicle traffic simulation application. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *821*, 12028. [CrossRef]
103. Rani, K.S.; Suguna, R.; Kumar, R.S.; Ram, P.S.; Haran, V.H. A smart AIS based portable wireless electric charging vehicles. *J. Phys. Conf. Ser.* **2021**, *1916*, 12145. [CrossRef]
104. Sumanasena, V.; Gunasekara, L.; Kahawala, S.; Mills, N.; De Silva, D.; Jalili, M.; Sierla, S.; Jennings, A. Artificial Intelligence for Electric Vehicle Infrastructure: Demand Profiling, Data Augmentation, Demand Forecasting, Demand Explainability and Charge Optimisation. *Energies* **2023**, *16*, 2245. [CrossRef]
105. Tabassum, T.; Khalghani, M.R. Cybersecurity Challenges in Microgrids: Inverter-Based Resources and Electric Vehicles. In *Power Systems Cybersecurity: Methods, Concepts, and Best Practices*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 91–114.
106. Elma, O.; Cali, U.; Kuzlu, M. An overview of bidirectional electric vehicles charging system as a Vehicle to Anything (V2X) under Cyber–Physical Power System (CPPS). *Energy Reports* **2022**, *8*, 25–32. [CrossRef]
107. Ahmad, F.; Ashraf, I.; Iqbal, A.; Marzband, M.; Khan, I. A novel AI approach for optimal deployment of EV fast charging station and reliability analysis with solar based DGs in distribution network. *Energy Rep.* **2022**, *8*, 11646–11660. [CrossRef]
108. Shurrab, M.; Singh, S.; Otrok, H.; Mizouni, R.; Khadkikar, V.; Zeineldin, H. An efficient vehicle-to-vehicle (v2v) energy sharing framework. *IEEE Internet Things J.* **2021**, *9*, 5315–5328. [CrossRef]
109. Kakkar, R.; Kumari, A.; Gupta, R.; Agrawal, S.; Tanwar, S. Artificial Neural Network and Game Theory for Secure Optimal Charging Station Selection for EVs. In Proceedings of the IEEE INFOCOM 2023-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Hoboken, NJ, USA, 20 May 2023; IEEE: Toulouse, France, 2023; pp. 1–6.
110. Vershinin, Y.A.; Pashchenko, F.; Olaverri-Monreal, C. *Technologies for Smart Cities*; Springer Nature: Berlin, Germany, 2022; ISBN 3031055160.
111. Silva, C.; Martins, F. Traffic flow prediction using public transport and weather data: A medium sized city case study. In *Trends and Innovations in Information Systems and Technologies*; Springer: Berlin/Heidelberg, Germany, 2020; Volume 28, pp. 381–390.
112. Zhao, J.; Xi, X.I.; Na, Q.I.; Wang, S.; Kadry, S.N.; Kumar, P.M. The technological innovation of hybrid and plug-in electric vehicles for environment carbon pollution control. *Environ. Impact Assess. Rev.* **2021**, *86*, 106506. [CrossRef]
113. Piccialli, F.; Giampaolo, F.; Prezioso, E.; Crisci, D.; Cuomo, S. Predictive analytics for smart parking: A deep learning approach in forecasting of iot data. *ACM Trans. Internet Technol.* **2021**, *21*, 1–21. [CrossRef]
114. Shatnawi, N.; Al-Omari, A.A.; Al-Qudah, H. Optimization of bus stops locations using GIS techniques and artificial intelligence. *Procedia Manuf.* **2020**, *44*, 52–59. [CrossRef]
115. Abduljabbar, R.; Dia, H.; Liyanage, S.; Bagloee, S.A. Applications of artificial intelligence in transport: An overview. *Sustainability* **2019**, *11*, 189. [CrossRef]
116. Kumar, P.; Hariharan, K.; Manikandan, M.S.K. Hybrid long short-term memory deep learning model and Dijkstra's Algorithm for fastest travel route recommendation considering eco-routing factors. *Transp. Lett.* **2023**, *15*, 926–940.
117. Nousias, S.; Tselios, C.; Bitzas, D.; Amaxilatis, D.; Montesa, J.; Lalos, A.S.; Moustakas, K.; Chatzigiannakis, I. Exploiting gamification to improve eco-driving behaviour: The GamECAR approach. *Electron. Notes Theor. Comput. Sci.* **2019**, *343*, 103–116. [CrossRef]
118. Ghaffarpasand, O.; Jahromi, A.M.; Maleki, R.; Karbassiyazdi, E.; Blake, R. Intelligent geo-sensing for moving toward smart, resilient, low emission, and less carbon transport. In *Artificial Intelligence and Data Science in Environmental Sensing*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 39–55.

119. Tselios, C.; Nousias, S.; Bitzas, D.; Amaxilatis, D.; Akrivopoulos, O.; Lalos, A.S.; Moustakas, K.; Chatzigiannakis, I. Enhancing an eco-driving gamification platform through wearable and vehicle sensor data integration. In Proceedings of the Ambient Intelligence: 15th European Conference, AmI 2019, Rome, Italy, 13–15 November 2019; Proceedings 15. Springer: Berlin/Heidelberg, Germany, 2019; pp. 344–349.
120. Delnevo, G.; Di Lena, P.; Mirri, S.; Prandi, C.; Salomoni, P. On combining Big Data and machine learning to support eco-driving behaviours. *J. Big Data* **2019**, *6*, 1–15. [CrossRef]
121. Boru İpek, A. Multi-Objective Simulation Optimization Integrated with Analytic Hierarchy Process and Technique for Order Preference by Similarity to Ideal Solution for Pollution Routing Problem. *Transp. Res. Rec.* **2023**, *2677*, 1658–1674. [CrossRef]
122. Mandžuka, S. Cooperative systems in traffic technology and transport. In *New Technologies, Development and Application 4*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 299–308.
123. Zhou, J. Research on Multi-objective Green Vehicle Path Optimization Based on Whale Algorithm. In Proceedings of the 2023 International Conference on Networking, Informatics and Computing (ICNETIC), Palermo, Italy, 29–31 May 2023; pp. 385–389.
124. Fernández, E.I.; Kühne, N.G.; Mulero, N.B.; Jara, A.J. Advancing Sustainability Impact Assessment: A Comprehensive Tool for Low Emissions Zone Management. In Proceedings of the 2023 8th International Conference on Smart and Sustainable Technologies (SpliTech), Bol, Hotel Elaphusa, 20–23 June 2023; pp. 1–6.
125. Gong, K. Research and analysis on technical problems of new energy vehicles in China based on big data and artificial intelligence algorithm. *J. Phys. Conf. Ser.* **2021**, *2138*, 12020. [CrossRef]
126. Manoharan, D.S. An improved safety algorithm for artificial intelligence enabled processors in self driving cars. *J. Artif. Intell. Capsul. Networks* **2019**, *1*, 95–104. [CrossRef]
127. Miao, Y.; Qiu, Z.; Zhang, M.; He, B.; Zhang, X.; Li, M. Integrated artificial intelligence and life cycle assessment to predict environmental and economic impacts for natural gas hybrid electric vehicle with multi-dimension. *J. Phys. Conf. Ser.* **2022**, *2198*, 12016. [CrossRef]
128. Ali, S.S.; Choi, B.J. State-of-the-art artificial intelligence techniques for distributed smart grids: A review. *Electronics* **2020**, *9*, 1030. [CrossRef]
129. Lytras, M.D.; Chui, K.T. The recent development of artificial intelligence for smart and sustainable energy systems and applications. *Energies* **2019**, *12*, 3108. [CrossRef]
130. You, S.; Zhao, Y.; Mandich, M.; Cui, Y.; Li, H.; Xiao, H.; Fabus, S.; Su, Y.; Liu, Y.; Yuan, H. A review on artificial intelligence for grid stability assessment. In Proceedings of the 2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Virtual, 11–13 November 2020; pp. 1–6.
131. Hussain, M.; Dhimish, M.; Titarenko, S.; Mather, P. Artificial neural network based photovoltaic fault detection algorithm integrating two bi-directional input parameters. *Renew. Energy* **2020**, *155*, 1272–1292. [CrossRef]
132. Ahmad, T.; Chen, H.; Shah, W.A. Effective bulk energy consumption control and management for power utilities using artificial intelligence techniques under conventional and renewable energy resources. *Int. J. Electr. Power Energy Syst.* **2019**, *109*, 242–258. [CrossRef]
133. Seh, Z.W.; Jiao, K.; Castelli, I.E. Artificial intelligence and machine learning in energy storage and conversion. *Energy Adv.* **2023**, *2*, 1237–1238. [CrossRef]
134. Zhou, S.; Hu, Z.; Gu, W.; Jiang, M.; Zhang, X.-P. Artificial intelligence based smart energy community management: A reinforcement learning approach. *CSEE J. Power Energy Syst.* **2019**, *5*, 1–10. [CrossRef]
135. Darab, C.; Tarnovan, R.; Turcu, A.; Martineac, C. Artificial intelligence techniques for fault location and detection in distributed generation power systems. In Proceedings of the 2019 8th International Conference on Modern Power Systems (MPS), Cluj Napoca, Romania, 21–23 May 2019; pp. 1–4.
136. Arrieta, A.B.; Díaz-Rodríguez, N.; Del Ser, J.; Bennetot, A.; Tabik, S.; Barbado, A.; García, S.; Gil-López, S.; Molina, D.; Benjamins, R. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion* **2020**, *58*, 82–115. [CrossRef]
137. Xu, Y.; Ahokangas, P.; Louis, J.-N.; Pongrácz, E. Electricity market empowered by artificial intelligence: A platform approach. *Energies* **2019**, *12*, 4128. [CrossRef]
138. Sulaiman, A.; Nagu, B.; Kaur, G.; Karuppaiah, P.; Alshahrani, H.; Reshan, M.S.A.; AlYami, S.; Shaikh, A. Artificial Intelligence-Based Secured Power Grid Protocol for Smart City. *Sensors* **2023**, *23*, 8016. [CrossRef]
139. Omitaomu, O.A.; Niu, H. Artificial intelligence techniques in smart grid: A survey. *Smart Cities* **2021**, *4*, 548–568. [CrossRef]
140. Wang, H.; Li, Z.; Meng, Q. Design and Research of Smart Grid Based on Artificial Intelligence. In Proceedings of the 2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA), Changchun, China, 28–30 June 2023; pp. 1467–1471.
141. Zhao, X.; Guo, Y.; Guo, X.; Li, H. Artificial Intelligence Applications and Prospects for The Smart Grid. In Proceedings of the 2023 Panda Forum on Power and Energy (PandaFPE), Chengdu, China, 27–30 April 2023; pp. 1844–1848.
142. Davlyatov, S. Artificial Intelligence Techniques: Smart Way to Smart Grid. In Proceedings of the 2023 International Conference on Artificial Intelligence and Smart Communication (AISC), Greater Noida, India, 27–29 January 2023; IEEE: Toulouse, France, 2023; pp. 838–842.
143. Onen, A. Role of artificial intelligence in smart grids. *Electr. Eng.* **2022**, *104*, 231. [CrossRef]

144. Yadeo, D.; Sen, S.; Saxena, V. Smart grid: Solid-state transformer and load forecasting techniques using artificial intelligence. In *Artificial Intelligence and Machine Learning in Smart City Planning*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 181–197.
145. Fang, X.; Lai, Y.; Fan, L.; Sun, Z.; Wang, Y.; Xuan, Y. Power grid user asset value evaluation method and application under the background of artificial intelligence and smart grid. *J. Comput. Methods Sci. Eng.* **2023**, *23*, 351–360. [CrossRef]
146. Khan, A.A.; Laghari, A.A.; Rashid, M.; Li, H.; Javed, A.R.; Gadekallu, T.R. Artificial intelligence and blockchain technology for secure smart grid and power distribution Automation: A State-of-the-Art Review. *Sustain. Energy Technol. Assess.* **2023**, *57*, 103282.
147. Rodgers, W.; Cardenas, J.A.; Gemoets, L.A.; Sarfi, R.J. A smart grids knowledge transfer paradigm supported by experts' throughput modeling artificial intelligence algorithmic processes. *Technol. Forecast. Soc. Chang.* **2023**, *190*, 122373. [CrossRef]
148. Khan, M.A.; Saleh, A.M.; Waseem, M.; Sajjad, I.A. Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment. *IEEE Access* **2022**, *11*, 1477–1505. [CrossRef]
149. 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**, *15*, 6488. [CrossRef]
150. Khosrojerdi, F.; Akhigbe, O.; Gagnon, S.; Ramirez, A.; Richards, G. Integrating artificial intelligence and analytics in smart grids: A systematic literature review. *Int. J. Energy Sect. Manag.* **2021**, *16*, 318–338.
151. Kumar, R.S.; Saravanan, S.; Pandiyan, P.; Tiwari, R. Impact of artificial intelligence techniques in distributed smart grid monitoring system. In *Smart Energy and Electric Power Systems*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 79–103.
152. Chaurasia, K.; Kamath, H.R. Artificial Intelligence and Machine Learning Based: Advances in Demand-Side Response of Renewable Energy-Integrated Smart Grid. In Proceedings of the Smart Systems: Innovations in Computing: Proceedings of SSIC 2021; Springer: Berlin/Heidelberg, Germany, 2022; pp. 195–207.
153. Slama, S. Ben Prosumer in smart grids based on intelligent edge computing: A review on Artificial Intelligence Scheduling Techniques. *Ain Shams Eng. J.* **2022**, *13*, 101504. [CrossRef]
154. Zambrano, A.F.; Giraldo, L.F. Solar irradiance forecasting models without on-site training measurements. *Renew. Energy* **2020**, *152*, 557–566. [CrossRef]
155. Ruhnau, O.; Hennig, P.; Madlener, R. Economic implications of forecasting electricity generation from variable renewable energy sources. *Renew. Energy* **2020**, *161*, 1318–1327. [CrossRef]
156. Dutta, S.; Sadhu, P.K.; Cherikuri, M.; Mohanta, D.K. Application of artificial intelligence and machine learning techniques in island detection in a smart grid. *Intell. Renew. Energy Syst.* **2022**, 79–109. [CrossRef]
157. Xin, C.; Yu, Z.; Yu, J.; Bian, J.; Cao, Q. Application of Smart Grid Energy Storage Technology Based on Artificial Intelligence Technology. In Proceedings of the 2021 3rd International Conference on Artificial Intelligence and Advanced Manufacture, Manchester, UK, 23–25 October 2021; pp. 1483–1487.
158. Liu, Z.; Gao, Y.; Liu, B. An artificial intelligence-based electric multiple units using a smart power grid system. *Energy Rep.* **2022**, *8*, 13376–13388. [CrossRef]
159. Yun, J.J.; Zhao, X.; Ma, L.; Liu, Z.; Yang, B. Open innovation dynamics and evolution in the mobile payment industry–comparative analysis among Daegu, Cardiff, and Nanjing. *Eur. Plan. Stud.* **2023**, *31*, 862–884. [CrossRef]
160. Gönenç, A.; Acar, E.; Demir, İ.; Yılmaz, M. Artificial Intelligence Based Regression Models for Prediction of Smart Grid Stability. In Proceedings of the 2022 Global Energy Conference (GEC), Batman, Turkey, 26–29 October 2022; pp. 374–378.
161. Ucar, F. A Comprehensive Analysis of Smart Grid Stability Prediction along with Explainable Artificial Intelligence. *Symmetry* **2023**, *15*, 289. [CrossRef]
162. Zheng, L.; Zhang, S.; Huang, H.; Liu, R.; Cai, M.; Bian, Y.; Chang, L.; Du, H. Artificial intelligence-driven rechargeable batteries in multiple fields of development and application towards energy storage. *J. Energy Storage* **2023**, *73*, 108926. [CrossRef]
163. He, Z.; Guo, W.; Zhang, P. Performance prediction, optimal design and operational control of thermal energy storage using artificial intelligence methods. *Renew. Sustain. Energy Rev.* **2022**, *156*, 111977. [CrossRef]
164. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M. Machine Learning-and Artificial Intelligence-Derived Prediction for Home Smart Energy Systems with PV Installation and Battery Energy Storage. *Energies* **2023**, *16*, 6613. [CrossRef]
165. Chakrapani, K.; Kavitha, T.; Safa, M.I.; Kempanna, M.; Chakrapani, B. Applications of Artificial Intelligence in Intelligent Combustion and Energy Storage Technologies. In *Applications of Big Data and Artificial Intelligence in Smart Energy Systems*; River Publishers: Roma, Italy, 2023; pp. 27–45.
166. Long, H.U.O.; Zhang, Y.; Xin, C. Artificial Intelligence Applications in Distributed Energy Storage Technologies. *Power Gener. Technol.* **2022**, *43*, 707.
167. Zehra, S.S.; Rahman, A.U.; Armghan, H.; Ahmad, I.; Ammara, U. Artificial intelligence-based nonlinear control of renewable energies and storage system in a DC microgrid. *ISA Trans.* **2022**, *121*, 217–231. [CrossRef] [PubMed]
168. Abdalla, A.N.; Nazir, M.S.; Tao, H.; Cao, S.; Ji, R.; Jiang, M.; Yao, L. Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview. *J. Energy Storage* **2021**, *40*, 102811. [CrossRef]
169. Athari, M.H.; Ardehali, M.M. Operational performance of energy storage as function of electricity prices for on-grid hybrid renewable energy system by optimized fuzzy logic controller. *Renew. Energy* **2016**, *85*, 890–902. [CrossRef]
170. Zahedi, R.; Ardehali, M.M. Power management for storage mechanisms including battery, supercapacitor, and hydrogen of autonomous hybrid green power system utilizing multiple optimally-designed fuzzy logic controllers. *Energy* **2020**, *204*, 117935. [CrossRef]

171. Yunhao, H.; Xin, C.; Erde, W.; Jianfeng, C.; Tingting, H.; Yang, M. Hierarchical control strategy for distributed energy storage units in isolated DC microgrid. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 7410–7415.
172. Franco, A.A.; Barnard, A.S. Artificial Intelligence in Electrochemical Energy Storage. *Batter. Supercaps* **2022**, *5*, e202200149. [CrossRef]
173. Lee, D.; Ooka, R.; Matsuda, Y.; Ikeda, S.; Choi, W. Experimental analysis of artificial intelligence-based model predictive control for thermal energy storage under different cooling load conditions. *Sustain. Cities Soc.* **2022**, *79*, 103700. [CrossRef]