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Review

Leveraging Artificial Intelligence to Bolster the Energy Sector in Smart Cities: A Literature Review

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Abstract: As Smart Cities development grows, deploying advanced technologies, such as the Internet of Things (IoT), Cyber–Physical Systems, and particularly, Artificial Intelligence (AI), becomes imperative for efficiently managing energy resources. These technologies serve to coalesce elements of the energy life cycle. By integrating smart infrastructures, including renewable energy, electric vehicles, and smart grids, AI emerges as a keystone, improving various urban processes. Using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and the Scopus database, this study meticulously reviews the existing literature, focusing on AI technologies in four principal energy domains: generation, transmission, distribution, and consumption. Additionally, this paper shows the technological gaps when AI is implemented in Smart Cities. A total of 122 peer-reviewed articles are analyzed, and the findings indicate that AI technologies have led to remarkable advancements in each domain. For example, AI algorithms have been employed in energy generation to optimize resource allocation and predictive maintenance, especially in renewable energy. The role of AI in anomaly detection and grid stabilization is significant in transmission and distribution. Therefore, the review outlines trends, high-impact articles, and emerging keyword clusters, offering a comprehensive analytical lens through which the multifaceted applications of AI in Smart City energy sectors can be evaluated. The objective is to provide an extensive analytical framework that outlines the AI techniques currently deployed and elucidates their connected implications for sustainable development in urban energy. This synthesis is aimed at policymakers, urban planners, and researchers interested in leveraging the transformative potential of AI to advance the sustainability and efficiency of Smart City initiatives in the energy sector.

Keywords: smart cities; energy sector; artificial intelligence

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1. Introduction

The concept of Smart Cities can be interpreted in many different ways, which highlights the importance of having a universally accepted definition. An example of this is highlighted in [1], where the concept of "smartness" in the context of Smart Cities is addressed as the unification of sustainability objectives, which ensures that technology integration serves a purpose beyond mere automation and actively engages users in achieving environmental goals. However, it is also recognized that the definition of Smart Cities is flexible and can be adapted to suit specific situations and contextual factors [2]. The integration of communication and information technologies in Smart Cities offers a wide range of potential benefits. The primary objective of Smart Cities is to effectively manage resources and achieve efficient energy consumption while facilitating seamless data communication to ensure smooth Smart City operations [3]. To cope with increasing power demands while protecting citizens from the detrimental effects of Greenhouse Gases (GHGs) emissions, it becomes crucial to monitor and manage energy in an efficient manner throughout its entire life cycle, which encompasses generation, transmission, distribution, and consumption processes. By adopting comprehensive energy management strategies, Smart Cities can play a pivotal role in promoting sustainability and mitigating environmental impacts [4]. Indeed, the integration of smart energy management is vital to further enhance the efficiency of Smart Cities. This integration can be achieved through the incorporation of Artificial Intelligence (AI) techniques. AI has the potential to significantly contribute to the performance and integration of alternative energy sources within the Smart City infrastructure. By leveraging AI algorithms, smart energy management systems can intelligently analyze large amounts of data from various sources, including renewable energy generation, energy consumption patterns, weather conditions, and demand forecasts. This enables the optimization of energy distribution and consumption, leading to more efficient utilization of resources and reduced reliance on traditional fossil fuel-based energy sources. AI also plays a crucial role in enhancing the integration of renewable energy into the existing energy grid. With its ability to adapt and learn from real-time data, AI can dynamically adjust energy distribution and storage strategies, ensuring the seamless integration of fluctuating renewable energy sources like solar and wind power. Furthermore, AI-driven predictive analytics can aid in anticipating energy demand fluctuations and identifying potential areas for energy savings and optimization. This empowers Smart Cities to proactively manage energy resources, reduce waste, and minimize carbon emissions, contributing to a more sustainable and eco-friendly urban environment. The incorporation of AI techniques into smart energy management systems holds significant promise for improving alternative energy performance and integration in Smart Cities, fostering a more sustainable and energy-efficient future [5]. Various AI algorithms are currently under study and review for diverse applications in industries that have shown increasing interest in them. This includes the implementation of the Smart City concept [2].

One of the definitions of AI can be found in [6]. In this context, the concept of Artificial Intelligence (AI) is initially defined as the capacity of an entity to function effectively in response to its environment. Therefore, AI involves the development of machines endowed with this characteristic, enabling them to perform functions within their environment, effectively mechanizing human thought processes.

In the domain of energy systems, AI finds several valuable applications. In particular, it can be employed for energy management to achieve savings, enable control functions, and optimize the forecasting of alternative energy generation. AI also facilitates accurate demand forecasting, consumption prediction, and the efficient monitoring of energy grids, contributing to enhanced operational efficiency and sustainability in the context of Smart Cities and beyond [7]. Therefore, the use of AI methods is an important tool to be used to improve different stages of the energy cycle in Smart Cities. AI has some important features that can be used in the energy sector, as shown below:

1. Learning: This aspect of AI relies on data collection and analysis to create algorithms that facilitate the development of efficiency-promoting processes. By processing large data sets, AI systems can identify patterns, trends, and correlations, enabling them to learn from past experiences and make informed decisions.
2. Cognition: The cognitive capabilities of AI help to recognize similarities and patterns in previous processes. Drawing on past experience and knowledge, AI can interpret complex data, recognize trends, and generate valuable insights, improving decision-making processes.
3. Actions: AI is capable of making automatic decisions within specified time frames. This involves the real-time processing of data to generate responses and take actions based on predetermined rules or learned behaviors. Such automation can streamline various tasks, leading to increased efficiency and precision. These fundamental AI functionalities play a crucial role in a wide array of industries, including energy management in Smart Cities, predictive analytics, natural language processing, robotics, and more. As AI continues to advance, its potential for transformative impact across diverse fields remains substantial [8].

To recognize the main elements in which Artificial Intelligence helps Smart Cities in the generation, transmission, distribution, and consumption of energy, the following questions are formulated for answering through the literature review:

- How can the implementation of AI methods address crucial challenges in the energy sector?
- What AI methodologies are currently being employed in Smart Cities to address challenges in the energy sector?
- What advantages does the application of AI in the energy sector offer that conventional methods cannot achieve?
- What are the latest trends in applying AI in Smart Cities to improve the energy sector?

This paper presents a review of the literature conducted using the Scopus search engine employing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. PRISMA primarily focuses on the reporting of reviews evaluating the effects of interventions but can also be used as a basis for reporting systematic reviews with objectives other than evaluating interventions [9]. This methodology is a guideline for writing clear, detailed reports on systematic reviews and meta-analyses, ensuring transparency and reliability. The guidelines include a Title and Abstract, which should be clear and concise, summarizing the reviewer's goals, methods, results, and conclusions. The Introduction section explains the rationale and objectives of the review. The Methods section describes the criteria for selecting studies and the data collection and analysis methods. In the Results section, the study selection process is illustrated (often with a flow chart), together with the characteristics of the studies and the main findings. The Discussion section interprets the results, considering the strengths and weaknesses of the evidence, and discusses the generalizability and applicability of the findings. PRISMA also assists authors in ensuring that they include all essential information and improve the transparency of their review or analysis. This research focuses on the utilization of Artificial Intelligence (AI) in the energy sector for Smart Cities. This includes the use of AI for control, the integration of renewable energy, smart grids, energy production, and the forecasting of energy consumption, as well as other AI applications. As the main results, statistical information is presented, such as the annual scientific production, most relevant sources, most cited articles, most relevant words, and keyword co-occurrence. These results can help in visualizing the trend of publications for each category, identifying areas of opportunity for publications, identifying the main concepts that appear for each category, highlighting the potential of using AI in the energy sector, and showing some case studies where it has been successfully implemented.

This document is divided into four main categories: energy generation, transmission, distribution, and consumption. Statistical data are presented about the annual publications, the most cited articles, and principal keywords. In addition, a keyword co-occurrence network is presented for each section in order to recognize the main concepts of each category and the relationship between the principal topics.

2. Methodology

This research article employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) as the proposed methodology. PRISMA 2020 offers effective reporting guidance for systematic literature reviews. The PRISMA method can be summarized using the chart presented in Figure 1. The initial phase involves the identification and screening of relevant papers to be included in the research. The exploration of articles was conducted by performing a comprehensive search on Scopus using specific terms related to "Smart Cities". The search targeted these terms within the title, abstract, and keywords of the articles. In addition, the following terms are used: "**AND** Energy **AND** Artificial Intelligence **OR** AI" (*Smart Cities-Energy-Artificial Intelligence*). The articles had to meet certain eligibility criteria, including being of the document type "journal" and published in English within the last ten years prior to conducting the research (from 2013 to 2023). Subsequently, the base search was repeated by incorporating additional terms, *Generation*, *Transmission*, *Distribution* and *Consumption*, including one term at a time after the term *Energy* of the base term. The potential articles identified during the initial search were subjected to a rigorous full-text review, and those that met all the specified criteria were included for further analysis. The subsequent phase involved data extraction and synthesis, which required retrieving relevant information using a standardized approach, including statistical meta-analysis. The search results derived from Scopus, with the base term, were exported and subjected to statistical analysis using the "Blibliometrix" software version 4.1.4. Additionally, a keyword co-occurrence network (KCN) was generated using the "VOSviewer" software version 1.6.19.

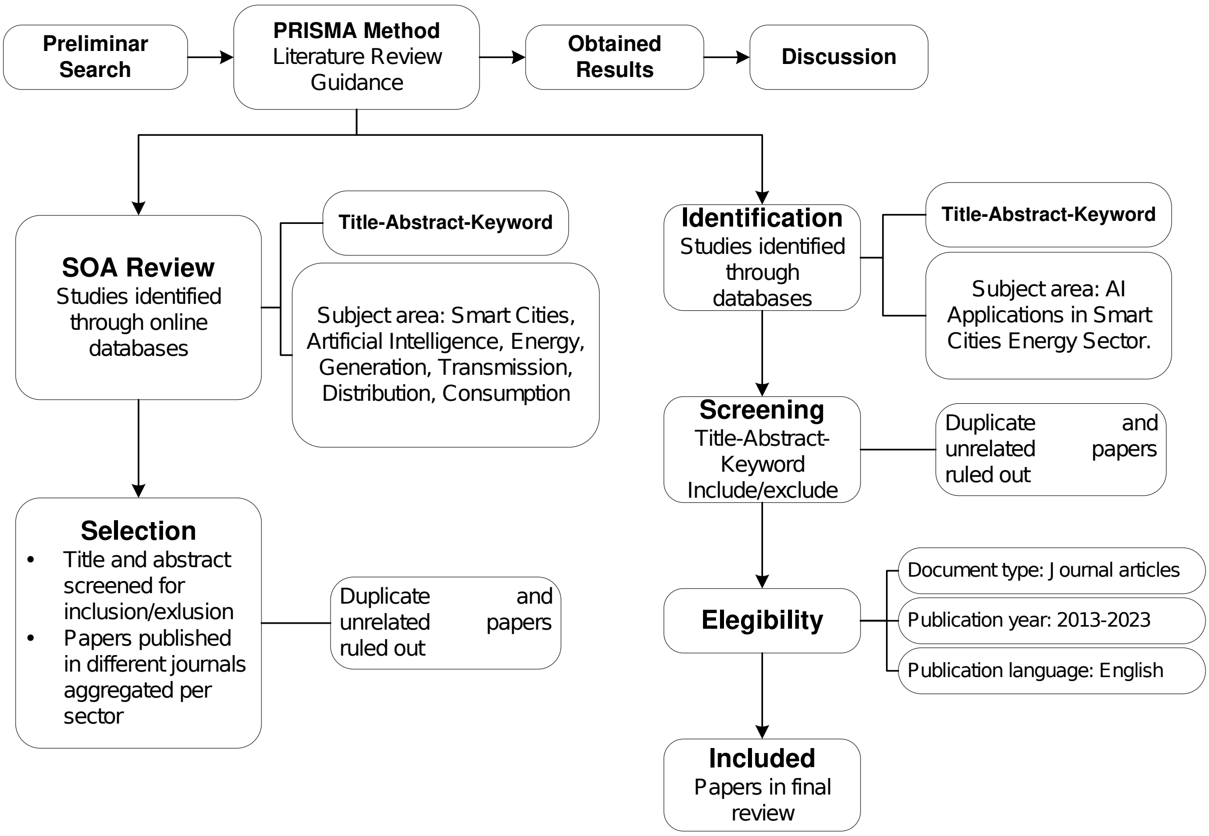

Figure 1. PRISMA method flowchart for paper inclusion/exclusion.

3. Results

3.1. Literature Review and Content Analysis

Using the methodology described in the previous section, the following results were obtained for the base terms. One way to easily analyze the results is by having a keyword co-occurrence network. Figure 2 shows a map made with the VOSviewer software; in this map, concepts such as IoT, energy efficiency, machine learning and smart grids are presented. A separate map was created for each category: energy generation, transmission, distribution and consumption. The purpose was to identify which category showed a higher prevalence of concepts in the overall map.

The following subsections analyze the statistical results of the search by adding a term each time, these terms being *Generation*, *Transmission*, *Distribution* and *Consumption*, in the *Smart City Energy* sector.

3.1.1. Energy Generation

The initial search was conducted on Scopus once more, incorporating the term "Generation" into the query. The search parameters were configured as follows: "Smart Cities" AND "Energy" AND "Generation" AND "Artificial Intelligence" OR "AI" (Smart Cities-Energy-

Generation-Artificial Intelligence). This yielded a total of 45 journal publications published since 2013. For this search, 35 sources were examined, involving 200 different authors.

Figure 3 illustrates the yearly scientific output on this subject. Given the relatively limited number of articles yielded by the initial search, the screening process primarily relied on keywords within titles and abstracts. However, a notable average annual growth rate of 42.62% was observed. The year 2023 has the highest publication count, totaling 12 publications. Notably, this observation was made at the midpoint of the year, suggesting the likelihood of additional publications during this period. This potential for further contributions could continue the upward trajectory in the research output.

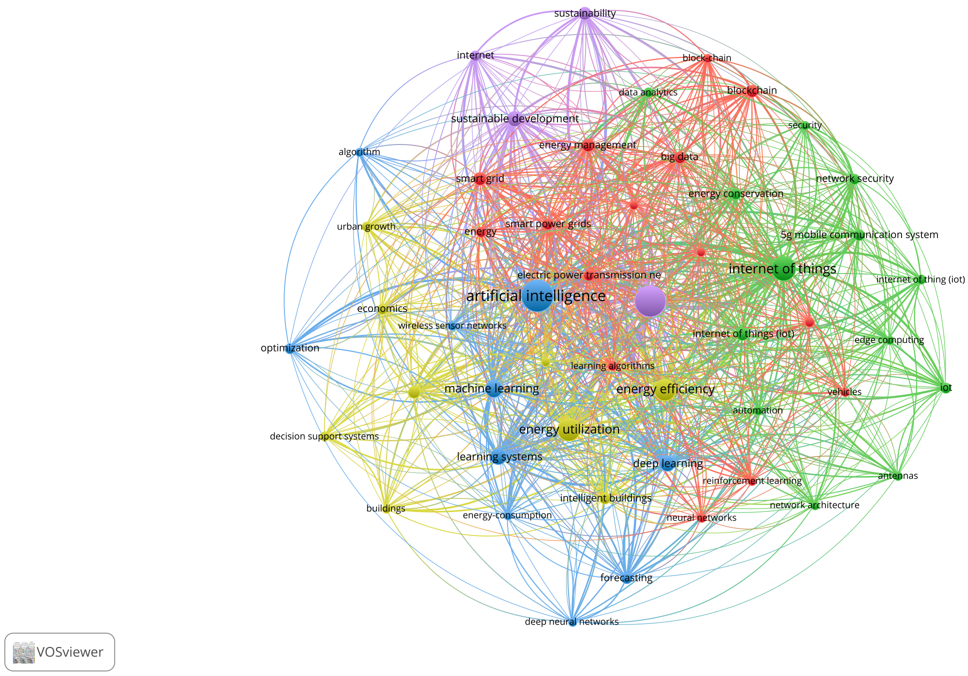

Figure 2. Keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy*.

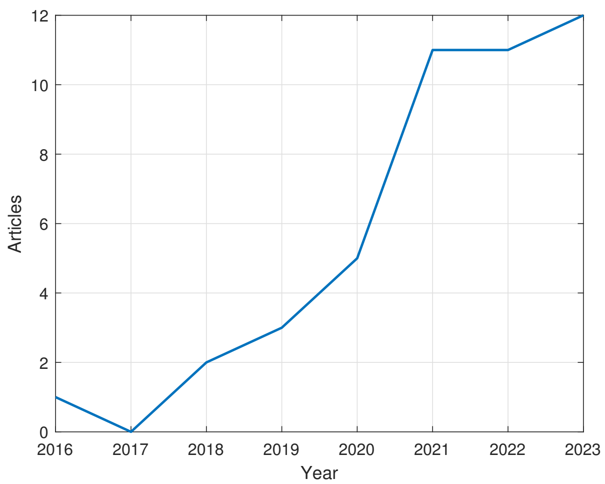

Figure 3. Annual scientific production (articles per year) for *Smart Cities-Artificial Intelligence-Energy-Generation*.

These publications involve authors from a variety of countries, the most prominent nationalities being China (38), India (20), Canada (12), the UK (12), Saudi Arabia (11), Iran (10), South Korea (10), the USA (10), Spain (9), and Japan (7). Additionally, when considering the number of citations received by articles originating from different countries, the leading nations are as follows: USA (423), China (127), South Korea (71), Romania (66), Turkey (36), India (29), South Africa (25), the United Kingdom (18), Qatar (14), and Bulgaria (6).

Table 1 shows the most relevant journals for paper publishing, exhibiting the number of articles published by each one of the journals, ranking in first place "Sustainable Cities and Society" with a total of 4 articles.

Table 1. Most relevant sources for *Smart Cities-Energy-Generation-Artificial Intelligence*.

Rank	Publisher	No. of Articles
1	*Sustainable Cities and Society*	4
2	*IEEE Access*	3
3	*Sensors*	3
4	*Applied Sciences*	2
5	*IET Smart Cities*	2

Table 2 shows the most cited articles worldwide for *Smart Cities-Artificial Intelligence-Energy Generation*. The most cited article is that of Ghadmai et al. with 75 citations, published in 2021 for *Sustainable Cities and Society*.

Table 2. Most globally cited articles published for *Smart Cities-Energy-Generation-Artificial Intelligence*.

Authors, Year	Title	Citations	Source
Ghadami N. et al. [2021] [10]	Implementation of solar energy in Smart Cities using an integration of artificial neural network, photovoltaic system, and classical Delphi methods	75	*Sustainable Cities and Society*
Serban AC. et al. [2020] [11]	Artificial Intelligence for smart renewable energy sector in Europe—smart energy infrastructures for next-generation Smart Cities	66	*IEEE Access*
Azzaoui AE, [2020] [12]	Block5GIntell: Blockchain for AI-enabled 5G networks	55	*IEEE Access*
Lee YL, [2021] [13]	6G massive radio access networks: Key applications, requirements and challenges	52	*IEEE Open Journal of Vehicular Technology*
Zhang, N., [2016] [14]	Semantic framework of Internet of Things for Smart Cities: Case studies	47	*Sensors*

The keyword search for *Smart Cities-Artificial Intelligence-Energy-Generation* yielded the following most common keywords: *Smart Cities* (23), *Artificial Intelligence* (19), *Internet of Things* (16), *Energy Utilization* (14), *Mobile Communication Systems* (11), *Energy Efficiency* (10), *Deep Learning* (9), *Learning Systems* (8), *Decision Making* (7), and *Economics* (7) as shown in Figure 4.

To analyze the word co-concurrency, VOSviewer software was utilized to generate a KCN (keyword co-concurrence network). Figure 5 shows the map obtained from the file with the Scopus search containing the data from articles previously referenced. This map or KCN shows that words like *sustainable development, decision making, and energy* are closely related to *Artificial Intelligence* and *energy generation*. While bigger nodes show the frequency of occurrence of each word as can be seen on the KCN, the biggest nodes (not containing *Smart Cities*) are *Internet of Things*, *learning systems*, *deep learning*, *mobile communications systems*, *energy utilization* and *energy efficiency*, which have the greatest occurrence, which coincides with the previous keyword analysis.

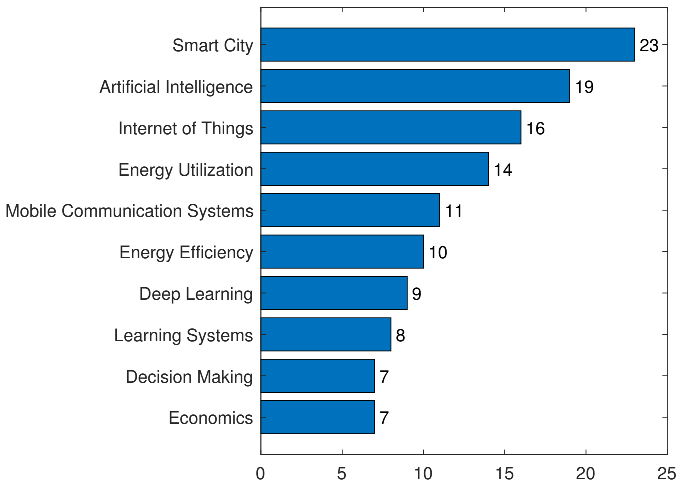

Figure 4. Most relevant words for *Smart Cities-Energy-Consumption-Artificial Intelligence*.

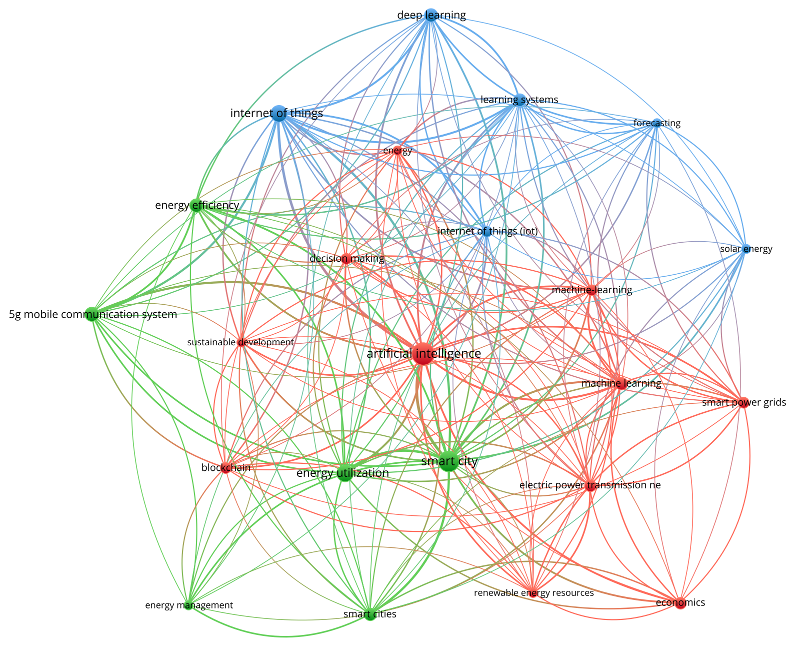

Figure 5. Keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Generation*.

3.1.2. Renewable Energy Sources within Smart Cities

To highlight the significance of renewable sources in previous years and their prospective impact in the coming years, a subsection was created under the category of Power Generation. This subsection is dedicated to underscoring the contribution of renewable energy sources. A search was performed on Scopus to identify the currently relevant topics and potential future trends in the use of two of the most widely adopted renewable energy sources, namely solar and wind energy, within the context of Smart Cities. The search query employed was as follows: "Smart Cities **AND** Energy **AND** Generation **AND** Solar **AND** Wind" (*Smart Cities-Energy-Generation-Solar-Wind*). For this search, the selected timeframe ranged from 2013 to 2023, and only journal publications in the English language were considered eligible. This search yielded a total of 47 articles, yet only 23 met the specified criteria outlined above. The average annual growth rate for this search is calculated at 1.84% from the start of the chosen period to its conclusion; this trend can be attributed to the publications between 2013 and 2016 showing a declining pattern. However, in subsequent years, there has been a consistent and continuous upward trend in the number of publications. Figure 6 illustrates the annual scientific production, revealing a significant increase in article output from 2013 to 2023. This underscores the recent upward trajectory in the field.

Indeed, it is crucial to recognize that at the time of composing this paper, there may still be forthcoming publications for 2023, rendering the final count for articles in this year subject to potential change. Concerning the search results, the volume of articles published on this topic emphasizes "Energy" as the most prominent source, boasting six articles. "Renewable Energy" closely follows with four articles, and "Energies" holds the third position with three articles, establishing these as the top three journals with the highest number of publications. Furthermore, Table 3 shows other notable sources identified in this search section.

Among the total of 47 published articles, the production per country indicates that India is the largest contributor to this renewable energy section, with 27 authors originating in this country. Saudi Arabia and China are closely behind, with 24 and 20 authors, respectively. Additionally, significant contributions are observed from authors hailing from Italy, with 18 of them. Furthermore, several countries have actively participated in this research area, including South Korea (12), the USA (8), Iran (6), Singapore (6), Canada (5), and the United Arab Emirates (5). This international involvement underscores the global significance and collaborative efforts in advancing knowledge related to renewable energy generation sources for applications in Smart Cities.

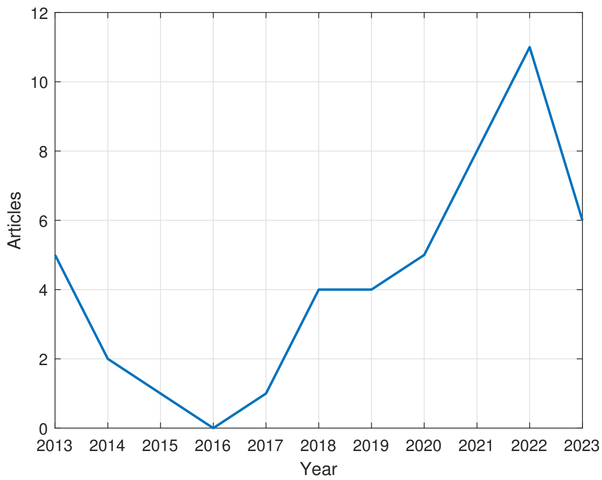

Figure 6. Annual scientific production for *Smart Cities-Energy-Generation-Solar-Wind*.

Table 3. Most relevant sources for *Smart Cities-Energy-Generation-Solar-Wind*.

Rank	Publisher	No. of Articles
1	*Energy*	6
2	*Renewable Energy*	4
3	*Energies*	3
4	*Energy Reports*	3
5	*Applied Energy*	2

Table 4 shows the articles from the search with the most citations; ref. [15] is the one that has the most citations.

From this search made, Figure 7 shows the most relevant words obtained; Renewable Energies (42) and Solar Power Generation (28) are the ones that appear the most in the search. Going deeper into the relevant words, it can also be seen that Smart City (16), Wind Power (16), and Smart Grid (15) also appear frequently in the articles. Economic Analysis (8) and Electric Power Transmission Networks (8) are also important concepts for the introduction of alternative energy sources, as they allow us to know the feasibility of an energy project and energy transportation, respectively. Sustainable Development (7) is also an important concept mentioned, as one of the main goals of these energy sources is to reach this sustainable development in Smart Cities and reduce fossil fuel dependency. Other relevant words are Power Generation (7) and Energy Storage (6).

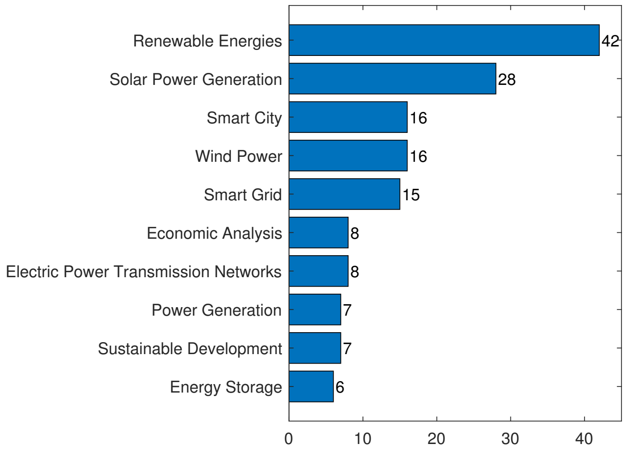

Figure 7. Most relevant words for *Smart Cities-Energy-Generation-Solar-Wind*.

Table 4. Most globally cited articles published for *Smart Cities-Energy-Generation-Solar-Wind*.

Authors, Year	Title	Citations	Source
Ramli Mam et al. [2018] [15]	Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm	345	*Renewable Energy*
Yang D. et al. [2013] [16]	Solar irradiance forecasting using spatial–temporal covariance structures and time-forward kriging	121	*Renewable Energy*
Oldenbroek V, et al. [2017] [17]	Fuel cell electric vehicle as a power plant: Fully renewable integrated transport and energy system design and analysis for Smart City areas	76	*International Journal of Hydrogen Energy*
De Luca G. et al. [2018] [18]	A renewable energy system for a nearly zero greenhouse city: Case study of a small city in southern Italy	51	*Energy*
Soliman Ms et al. [2021] [11]	Supervisory energy management of a hybrid battery/PV/tidal/wind sources integrated into a DC-microgrid energy storage system	42	*Energy Reports*

A KCN was obtained using VOSviewer by introducing the information obtained from the Scopus search. Figure 8 illustrates the KCN focusing on solar power generation and its interconnected nodes, including renewable energy, hybrid systems and electric power. Another important concept depicted in the KCN is wind power, highlighting the frequent association between smart grids, Smart Cities, and wind energy generation. This diagram serves as a valuable tool to analyze crucial topics related to the integration of renewable energies into Smart Cities. One notable relationship showcased in this diagram is the energy storage and photovoltaic systems. It exemplifies the essential role of storage devices in supporting the operation of photovoltaic systems. Additionally, the diagram features an economic analysis component closely tied to solar power generation. This economic analysis can be linked to the feasibility assessment of solar photovoltaic (PV) systems from a financial perspective. This type of graphical representation effectively illustrates associations between commonly co-searched keywords. An examination of data extracted from Bibliometrix reveals that topics such as energy utilization, economics, and greenhouse gases are currently capturing the attention of scientists as indicated by their relevance and ongoing development. These subjects are intricately linked to the global issue of climate change and represent a pressing global concern. Furthermore, emerging themes highlighted in the diagram include forecasting, deep learning, solar radiation, and weather stations. This aligns with the consensus that the use of renewable energy sources is key to achieving the Sustainable Development Goals. The prominence of Artificial Intelligence underscores its increasing relevance and growth in the current year. Overall, this KCN offers a comprehensive overview of the interconnections and areas of interest within renewable energy and Smart City development. It serves as a valuable resource for understanding the evolving landscape of sustainable energy solutions and their critical role in addressing global challenges such as climate change.

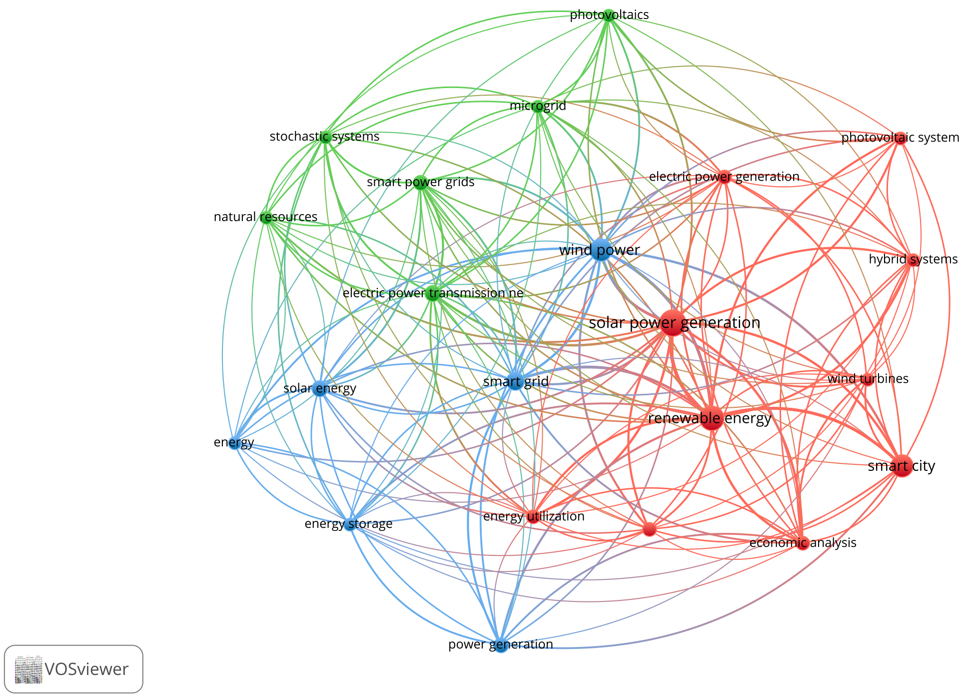

Figure 8. Keyword co-occurrence network for *Smart Cities-Energy-Generation-Solar-Wind*.

3.1.3. Energy Transmission

For the *Transmission* section, a Scopus search was performed by adding the aforementioned term to the base structure, resulting in "Smart Cities **AND** Energy **AND** Transmission **AND** Artificial Intelligence **OR** AI" (*Smart Cities-Energy-Transmission-Artificial Intelligence*. It has a total of 31 articles, with an average annual growth rate of 14 percent from the year 2013 to 2023. Figure 9 shows the Annual Scientific production. It is essential to note that the analysis excludes articles published from 2013 to 2015 for this specific topic or area, as there were no publications during that period. Therefore, the graph and statistics presented focus only on the years following 2015.

As is evident from the analysis, there is a clear tendency to increase the number of publications over time. However, it is noteworthy that there is a notable lack of publications specifically focused on energy transmission. It is essential to acknowledge that this paper's analysis was conducted before the end of 2023, leaving room for additional publications during the remaining part of the year. Therefore, the number of publications for 2023 may still witness growth, potentially shedding more light on the area of energy transmission in the context of Smart Cities. The most relevant sources are presented in Table 5, *IEEE Access*, *Sustainable Cities and Society*, *Wireless Communications and Mobile Computing* being the three sources with the most publications in this field, each having three publications.

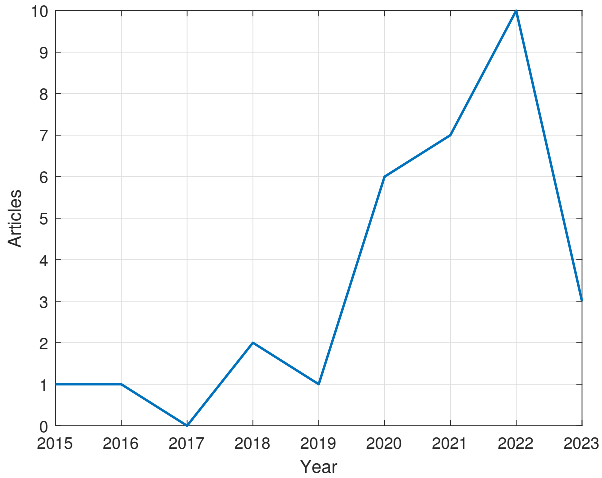

Figure 9. Annual scientific production of energy transmission keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Transmission*.

Table 5. Most relevant sources for *Smart Cities-Artificial Intelligence-Energy-Transmission*.

Rank	Publisher	No. of Articles
1	*IEEE Access*	3
2	*Sustainable Cities and Society*	3
3	*Wireless Communications and Mobile Computing*	3
4	*Sustainability*	2
5	*Computer Communications*	1

Indeed, it is crucial to highlight that China exhibits the highest number of authorships, with 29 articles featuring at least one Chinese author. Following closely are Germany and Saudi Arabia, each with 11 publications. South Korea and India also demonstrate a significant presence in the research, with 10 and 9 articles published by authors of their respective nationalities, respectively. Furthermore, countries such as France, Lebanon, the United Kingdom, and Malaysia, among others, have contributed to the research in the selected category, although to a lesser extent, each having eight articles. The diverse international participation underscores the global interest and participation in this subject matter.

Table 6 presents the articles with the most citations on this research. The work presented in [3] is the most cited, with 258 citations.

Table 6. Most globally cited articles published for *Smart Cities-Energy-Transmission-Artificial Intelligence*.

Authors, Year	Title	Citations	Source
Ullah N. et al. [2020] [3]	Applications of Artificial Intelligence and Machine learning in Smart Cities	258	*Computer Communications*
Serrano W. et al. [2018] [4]	Digital systems in Smart Cities and infrastructure	66	*Smart Cities*
Aguilar J. et al. [2021] [19]	A systematic literature review on the use of Artificial Intelligence in energy self-management in smart buildings.	53	*Renewable and Sustainable Energy Reviews*
Sharma H, [2021] [20]	Machine learning in wireless sensor networks for Smart Cities: a survey.	52	*Electronics*
Khan N., [2021] [21]	DB-Net: A novel dilated CNN-based multi-step forecasting model for power consumption in integrated local energy systems.	50	*International Journal of Electrical Power*

The most relevant words for *Smart Cities-Artificial Intelligence-Energy-Transmission* are presented using Figure 10, having *electric power transmission networks* (17) as the category with the highest occurrence. Other important concepts can be identified as *smart power grids* (12) and *Internet of Things* (11), which are part of AI and Smart City, which are part of the base structure.

The map obtained from *VOSviewer* with the information from the Scopus search is presented in Figure 11. A relationship between *Smart City* and *Artificial Intelligence* is shown; while *Smart City* is closely related to *Internet of Things* and *Energy Utilization*, on the other hand, AI is related to *Smart Power Grids*, and this word to *Electric Power Transmission networks*. These are interesting relationships, as smart power grids have AI applications in electric power transmission networks.

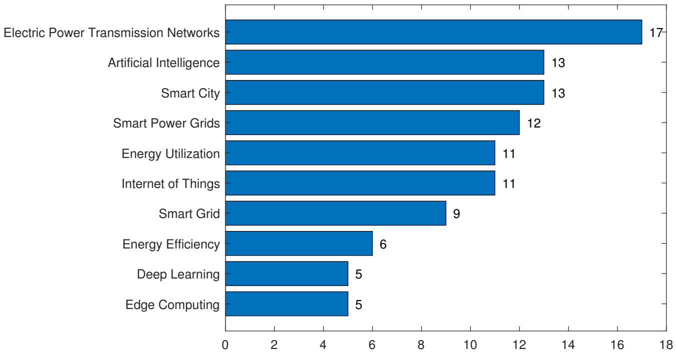

Figure 10. Most relevant words for *Smart Cities-Artificial Intelligence-Energy-Transmission*.

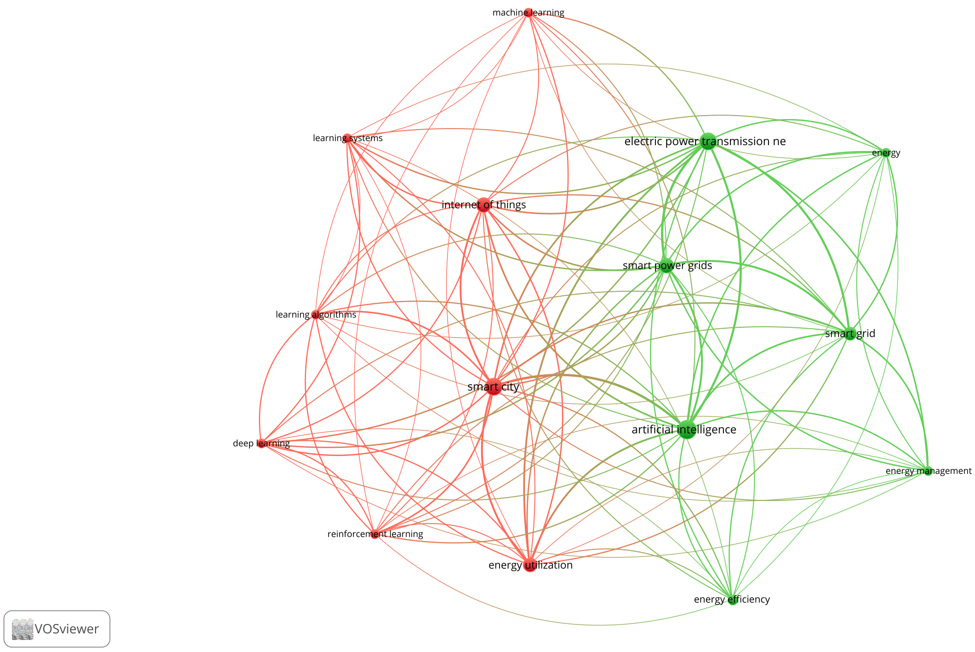

Figure 11. Keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Transmission*.

3.1.4. Energy Distribution

This time, a search on Scopus for the base structure was performed, adding *Distribution*, resulting in "Smart Cities **AND** Energy **AND** Distribution **AND** Artificial Intelligence **OR** AI" (*Smart Cities-Energy-Distribution-Artificial Intelligence*. A total of 21 articles were found, with an average annual growth rate of 10. 41% from 2013 to 2023. Figure 12 shows the annual scientific production; similarly to the *Energy Transmission* subsection, *Energy Distribution* has no reported articles found by Scopus from 2013 to 2016. For this reason, the previously mentioned years are not considered in Figure 12.

For the *Energy Distribution* topic, an intermittent pattern in the number of publications is identified, with notable fluctuations over the years. Specifically, there was an increase in the number of publications in 2019 and 2021, indicating a surge in research activity during those periods. However, a decrease in publication frequency was observed in 2020 and 2022. Additionally, as mentioned earlier, the year 2023 is subject to the constraint of limited publications in the area of energy transmission and distribution. This intermittent trend in research output underscores the dynamic nature of the field and suggests that further research is required to determine the factors influencing these fluctuations.

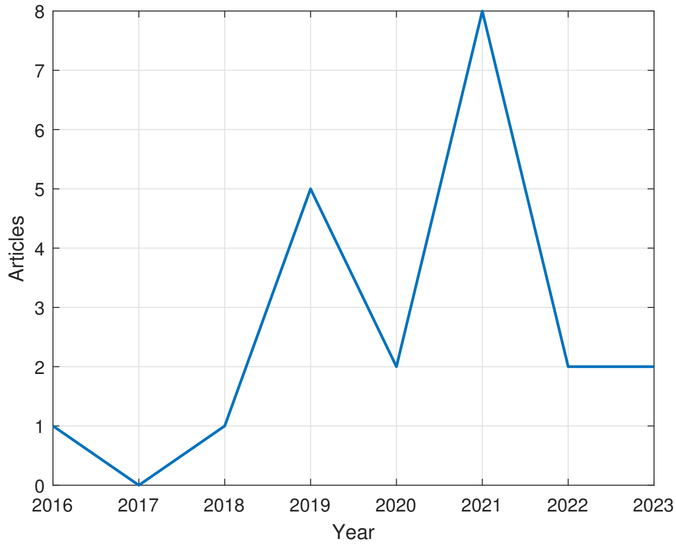

Figure 12. Annual scientific production of energy transmission keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Distribution*.

After analyzing the number of articles published regarding this topic, the most relevant source was *Sustainability* with four articles, followed by *Applied Sciences* with three. The most relevant sources of this section search are presented in Table 7.

Table 7. Most relevant sources for *Smart Cities-Artificial Intelligence-Energy-Distribution*.

Rank	Publisher	No. of Articles
1	*Sustainability*	4
2	*Applied Sciences*	3
3	*Energy and Buildings*	2
4	*Energy*	1
5	*Future Generation Computer Systems*	1

Upon analyzing production by country, China emerges as the leading contributor in the distribution section, with 18 articles authored by nationals. Following behind are Spain and Lebanon with eight and six articles, respectively. Noteworthy contributions are also observed from India, Japan, and Saudi Arabia, each with six articles, among several other countries that have actively participated in this area of research. The diverse international participation emphasizes the global interest and collaboration in advancing knowledge related to energy distribution within Smart Cities.

In Table 8 are presented the articles with the most citations of this research, with [22] being the most cited, having a total of 182 citations.

The most relevant words obtained for the distribution can be seen in Figure 13, being *Artificial Intelligence* (7) and *Smart Cities* (6). As they are part of the base search, some of the relevant words were *Energy Efficiency* (5) and *Data Analytics* (4). Energy efficiency is an important concept to consider for distribution networks since most articles seek to minimize energy losses to obtain better efficiency. For data analytics, it is important to monitor the distribution of energy, as AI could help to perform this task. Other relevant words are *Economics* (4) and *Deep Learning* (4).

A KCN was obtained using VOSviewer by feeding the information obtained from the Scopus search; Figure 14 shows this KCN. The KCN shows that the main topic is *Artificial Intelligence* which is connected to several nodes, such as *Learning Systems*, *Sustainability*, *Machine Learning*, and *Energy Efficiency*. This last keyword is connected to the second-highest co-occurrence word, which is *Smart Cities*, which shows that AI and Smart Cities are often paired with energy efficiency.

Table 8. Most globally cited articles published for *Smart Cities-Artificial Intelligence-Energy-Distribution*.

Authors, Year	Title	Citations	Source
Le L.T. et al. [2019] [22]	A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for Smart City planning	182	*Applied Sciences*
Idowu S. et al. [2016] [23]	Applied machine learning: Forecasting heat load in district heating system	152	*Energy and Buildings*
Zhou Z. et al. [2019] [24]	Blockchain and computational intelligence inspired incentive-compatible demand response in internet of electric vehicles	91	*IEEE Transactions on Emerging Topics in Computational Intelligence*
Le L.T, [2019] [25]	Estimating the heating load of buildings for Smart City planning using a novel Artificial Intelligence technique PSO-XGBoost.	71	*Applied Sciences*
Ingwersen, P., [2018] [26]	Smart City research 1990–2016.	36	*Scientometrics*

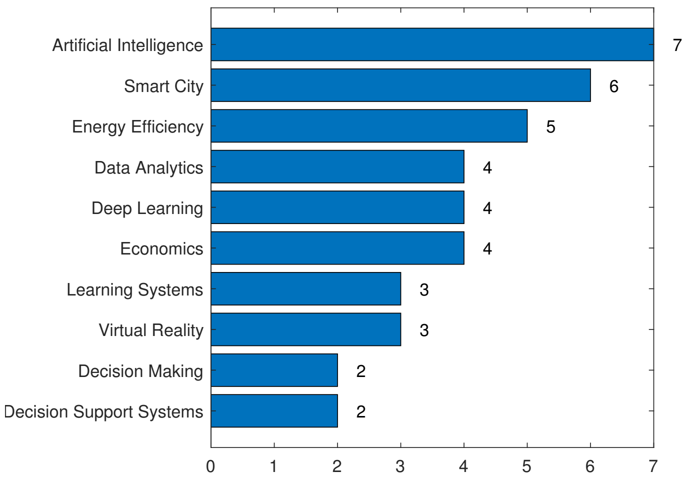

Figure 13. Most relevant words for *Smart Cities-Artificial Intelligence-Energy-Distribution*.

3.1.5. Energy Consumption

A search was conducted on Scopus for articles containing the terms "Smart Cities **AND** Energy **AND** Consumption **AND** Artificial Intelligence **OR** AI" (*Smart Cities-Energy-Consumption-Artificial Intelligence*). The results of the previously mentioned search show a total of 103 documents published from 2013 to 2023, having been published by 60 sources with a total of 432 authors. Figure 15 shows the number of articles published each year since 2014 (there were no publications during 2013); an interesting pattern can be observed in the publication trends. In 2015, there was a significant drop in the number of publications, reaching zero. However, in the subsequent years, there was a steady increase in the number of articles published, indicating a rising trend. Although 2023 shows a lower production number so far, it is essential to consider that the year has not concluded, leaving room for additional articles to be published, potentially continuing the upward trend from previous years.

The average annual growth rate for publications containing the specified terms stands at 35.11%, demonstrating a notable increase in research activity over time. Furthermore, the average number of citations per article is 27.54, highlighting the impact and relevance of the research output in this field. These metrics emphasize the significance and growing interest in the subject of AI applications in the energy sector within Smart Cities.

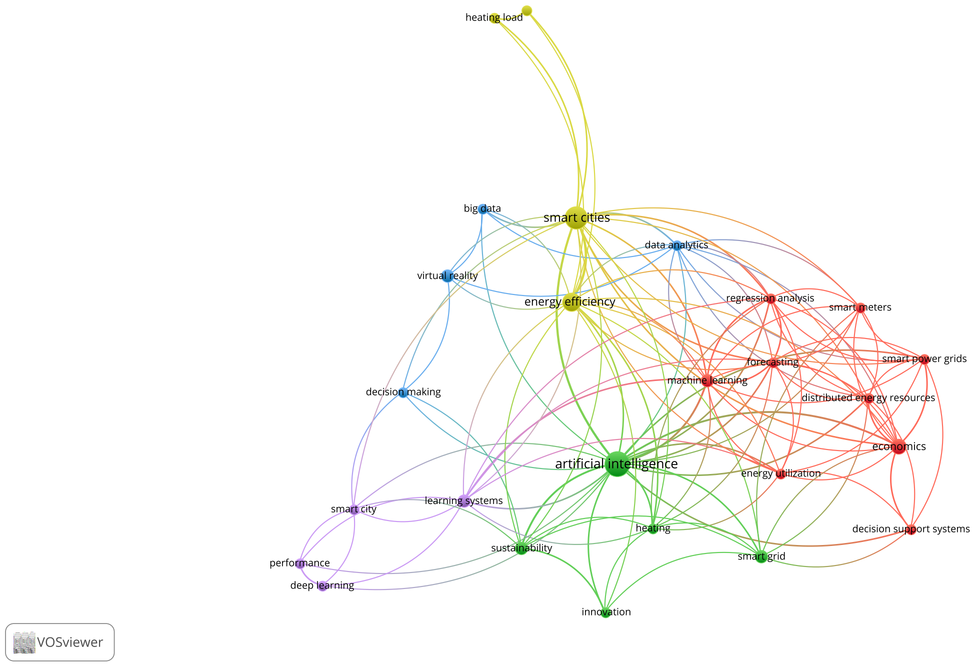

Figure 14. Keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Distribution*.

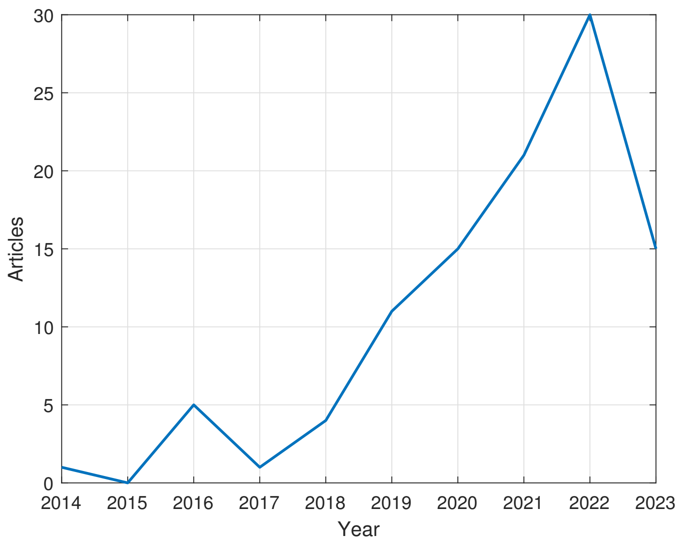

Figure 15. Annual scientific production (articles per year) for *Smart Cities-Artificial Intelligence-Energy-Consumption*.

The most relevant sources are presented in Table 9, IEEE Access (nine publications), Sustainable Cities and Society (with nine articles) and Sustainability (with six papers) are the three sources with the most publications in this field.

The publications encompass authors from various countries, with the most prevalent nationalities among the authors being China (109), the USA (32), India (31), Saudi Arabia (30), Spain (27), the United Kingdom (23), South Korea (21), Italy (11), Japan (11), and Canada (10), which comprise the top ten contributors in this category. In particular, South Korea stands out as the country with the highest number of citations, with an accumulated total of 148 citations for its contributions in this area. This indicates the significant impact and recognition of research conducted by authors from South Korea in the field of AI applications in the energy sector within Smart Cities. The wide array of contributing nations reflects the global interest and collaboration in advancing knowledge in this domain.

Table 9. Most relevant sources for *Smart Cities-Artificial Intelligence-Energy-Consumption*.

Rank	Publisher	No. of Articles
1	*IEEE Access*	9
2	*Sustainable Cities and Society*	9
3	*Sustainability*	6
4	*Energies*	5
5	*Sensors*	5

Table 10 shows the most globally cited articles for the period comprehended from 2014 to 2023 based on the search *Smart Cities-Artificial Intelligence-Energy-Consumption*. The article with the most citations is [27] with a total of 423 citations, which was published in *Applied Energy* in the year 2018.

Table 10. Most globally cited articles published for *Smart Cities-Artificial Intelligence-Energy-Consumption*.

Authors, Year	Title	Citations	Source
Rahman A., [2018] [27] *	Predicting electricity consumption for commercial and residential buildings using deep Recurrent Neural Networks	423	*Applied Energies*
Ullah, Z., [2020] [28]	Applications of Artificial Intelligence and machine learning in Smart Cities	258	*Computer Communications*
Alsamhi, S. [2019] [29]	Survey on collaborative smart drones and Internet of Things for improving smartness of Smart Cities	195	*IEEE Access*
Vázquez-Canteli, J. R., [2019] [30]	Fusing TensorFlow with building energy simulation for intelligent energy management in Smart Cities	113	*Sustainable Cities and Society*

* ref. [27] also appears in the search for energy generation but the topic better fits energy consumption.

The search for keywords related to *Smart Cities-Artificial Intelligence-Energy-Consumption* provided the following results: *Energy utilization* (73), *Artificial Intelligence* (56), *Smart City* (52), *Energy Efficiency* (30), *Internet Of Things* (25), *Learning Systems* (18), *Deep Learning* (15), *Sustainable Development* (14), *Decision Making* (10) and *Economics* occupy the top ten keywords results for this search.

As in all previous subsections, a KCN was performed using VOSviewer software, allowing to visualize the most frequent occurrence of a word and how often words are searched together. As previously mentioned, it can be corroborated using Figure 16. The analysis of the keyword frequency of occurrence reveals that terms such as “energy utilization”, “energy efficiency”, “Artificial Intelligence ”, “learning systems”, and “deep learning” are among the most frequently mentioned keywords. In the visual representation of the data, the larger nodes correspond to terms with the highest frequency of occurrence. On the other hand, terms with more links represent keywords with a greater co-occurrence with other terms. This graphical representation provides valuable insights into the prominence and relationships among the key concepts in the research domain of AI applications in the energy sector within Smart Cities.

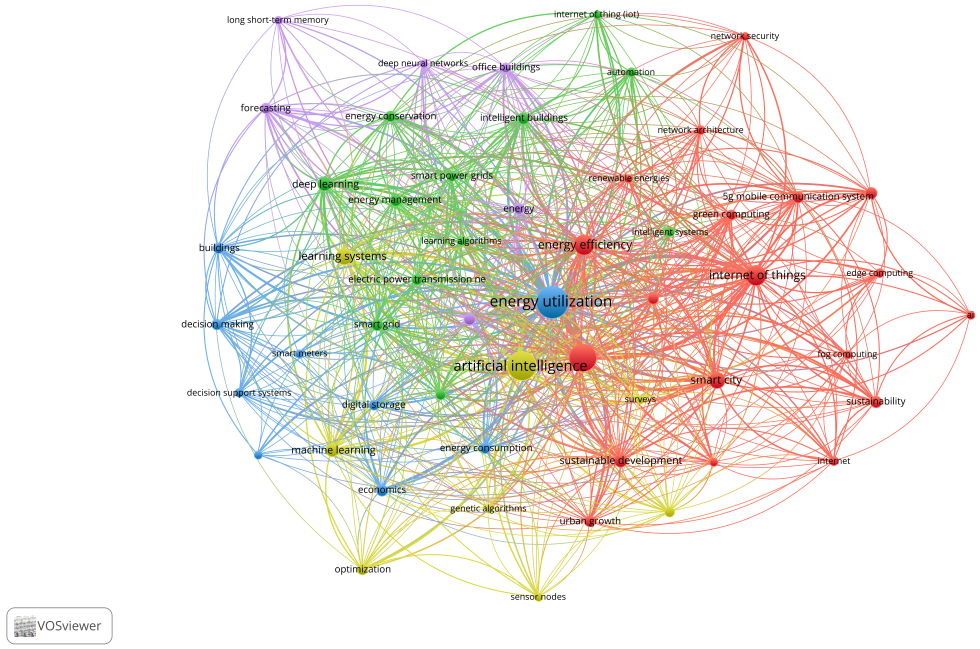

Figure 16. Keyword co-occurrence network for *Smart Cities-Artificial Intelligence-Energy-Consumption*.

4. Discussion

This section delves into a more detailed analysis of the selected papers that met all the specified eligibility criteria. Using the PRISMA methodology, this paper aims to provide a comprehensive overview of the existing literature on AI applications in the energy sector within Smart Cities. This systematic review allows to identify common patterns, consistencies, and trends in each category. By doing so, the reader can gain valuable insight into the advancements and developments within these research areas. The following subsections will present the findings for each of the topics in a structured and coherent manner.

Table 11 shows the articles obtained after screening and will be referred to in the following sections. The table presents the rich landscape of research in Smart Cities and energy applications, showcasing the evolution of methodologies and technologies over time. The diversity of the methods with which researchers have approached the areas described previously varies from algorithms of machine learning, fuzzy logic, optimization, and structural analyses; this diversity indicates the interdisciplinary nature of the research performed in the Smart Cities context and the application that AI has in the same area. Future research could focus on validating and standardizing approaches to ensure the compatibility and reproducibility of results in terms of real-world implementation. Possible areas of exploration include the scalability of the proposed solutions, addressing challenges in deployment and integration into existing urban infrastructure. Articles from the early years (2018–2020) showcase a keen interest in topics such as wind characterization, digital systems for transmission networks, and microgrid management. As emerging technologies continue to evolve, IoT technologies are becoming increasingly popular. This trend is evident in the table, where a search for the frequency of the term in the “Method” column shows a total of 13 occurrences, starting from the year 2020. Climate change is a pressing issue globally, as evidenced by the increasing number of papers on renewable energy being integrated into Smart Cities. It is highly recommended to continue research on renewable energy sources since this topic is still in its nascent stages and remains critical for achieving long-term energy goals and the Sustainable Development Goals (SDGs). The articles related to renewables focus on wind turbines, solar energy, hydrogen production, and renewable energy in high greenhouse-gas-emitting sectors. Methods include structural and modal analyses, fuzzy methods, social and political analysis, and optimization algorithms.

Table 11. Articles that fulfilled all eligibility criteria.

Area of Application	Author(s)	Year	Category	Method	Source
Generation	Miyasawa A. et al. [31]	2023	Demand forecasting	Smart metering, nonparametric regression models.	*IET Smart Cities*
Generation	Shafiullah M. et al. [32]	2023	Energy Systems	Artificial Intelligence, IoT	*Smart Cities*
Generation	Wu Z. et al. [33]	2023	Wind power forecasting	Probabilistic Physics-informed AI for completing dataset caused by ocassional shutdwon	*CMES—Computer Modeling in Engineering and Sciences*
Transmission	Fakhar A. et al. [34]	2023	Smart Grids with Renewable Energy	Cloud Computing, IoT, Blockchain	*International Journal of Green Energy*
Consumption	Bayer D. and Pruckner M. [35]	2023	Energy Systems in Buildings	Digital Twin	*Energy Informatics*
Consumption	Alymani M. et al. [36]	2023	Forecasting energy consumption	Stacked Autoencoder (SAE), Deep Neural Network (DNN), Bidirectional Long Short-Term Memory (BiLSTM)	*Sustainable Energy Technologies and Assessments*
Consumption	Al-Habaibeh A. et al. [37]	2023	Estimate crowds in cities	Internet of Things (IoT)	*Ain Shams Engineering Journal*
Consumption	Selvaraj R. et al. [38]	2023	Energy consumption management	Artifitial Intelligence Technique for Monitoring Systems in Smart Buildings (AIMS-SB)	*Sustainable Energy Technologies and Assessments*
Consumption	Feng Y. et al. [39]	2023	Energy Saving	Reinforcement Learning	*IEEE Access*
Consumption	Jiang R. et al. [40]	2023	Demand Prediction	Deep-chain echo state network (DCESN)	*IEEE Transactions on Industrial Informatics*
Consumption	AlHajri I. et al. [41]	2023	Urban Planning	Long-Short Term memory networks	*Energy*
Renewables	Fantin Irudaya Raj E. et al. [42]	2023	Wind turbines in smart cities	Structural, modal, and harmonic analyses performed using ANSYS	*MRS Energy and Sustainability*
Generation	Khan N. et al. [43]	2023	Power Generation Forecasting	Multi-Head Attention (MHA)-based deep Autoencoder(AE) with Extreme Gradient Boosting (XBG) algorithm	*IEEE Internet of Things Journal*
Renewables	Ulpiani G. et al. [44]	2023	Renewable energy in high GHG's emitting sectors in cities	Social and Political analysis	*Renewable and Sustainable Energy Reviews*
Renewables	Kedir N. et al. [45]	2023	Solar/PV Systems	Fuzzy Hybrid Methods	*Energies*
Consumption	Icaza-Alvarez D. et al. [46]	2023	Estimation on the power demand	Energy Plan tool	*Energy Reports*
Generation	Moon J. et al. [47]	2022	Electrical load forecasting	Explainable Electrical Load Forecasting (XELF) Methodology	*Sustainable Energy Technologies and Assessments*
Transmission	Said D. [48]	2022	Demand-Side Management	Big data, Blockchain, Machine learning (ML), IoT	*IEEE Engineering Management Review*
Generation	Heidari A. et al. [49]	2022	Smart cities power and energy management	Convolutional Neural Network (CNN) Long Short-Term Memory (LSTM)	*Sustainable Cities and Society*
Generation	Chang E.-C. et al. [50]	2022	PV tracking and control	Finite Time Terminal Attractor (FFTA)	*Wireless Communications and Mobile Computing*
Transmission	Liu Z. et al. [51]	2022	Smart Power Grids, Power Systems	Machine learning (ML)	*Energy Reports*
Transmission	Khosrojerdi F. et al. [52]	2022	Smart Grid	Artificial Intelligence Analytics (AIA)	*International Journal of Energy Sector Management*

Table 11. *Cont.*

Area of Application	Author(s)	Year	Category	Method	Source
Consumption	Chavhan S. et al. [53]	2022	Energy-efficient transport	AI-IoT System	*ACM Transactions on Internet Technology*
Consumption	Al-Hawawreh M. et al. [54]	2022	Smart decision making	Deep Reinforcement Learning (DRL)	*IEEE Sensors Journal*
Consumption	Singh S. et al. [55]	2022	Clustering for Wireless Sensors Networks	Improved gray wolf optimization (IGWO)	*Sensors*
Consumption	Huang J. et al. [56]	2022	Building energy forecast	Three ML algorithms (SVR, XGBoost, and LSTM)	*Applied Sciences*
Consumption	Mohamed H. et al. [57]	2022	Reduce energy consumption	TOPSIS fuzzy	*Electronics*
Consumption	Ren Y. et al. [58]	2022	Data management in energy consumption	Quantum-inspired Reinforcement Learning (QRL)	*IEEE Transactions on Green Communications and Networking*
Consumption	Murthy Nimmagadda S. and Harish K.S. [59]	2022	Building smart cities	Internet of Things (IoT), Connectivity, Cloud computing and AI	*Multimedia Tools and Applications*
Consumption	Islam N. et al. [60]	2022	Data management	Secured protocol with collaborative learning for IoT using AI techniques	*Sustainability*
Consumption	Zamponi M.E. and Barbierato E. [61]	2022	Forecast energy consumption	Different AI algorithms	*Smart Cities*
Consumption	Naveed Q.N. et al. [62]	2022	Transportation data management	Improved phase timing optimization (IPTO)	*Sensors*
Consumption	Akkad M.Z. et al. [63]	2022	Energy consumption and emissions	IoT, Smart bins, multi-percentage sensors	*Designs*
Consumption	Garlik B. [64]	2022	Energy consumption reduction in buildings	Artificial Intelligence with IoT	*Applied Sciences*
Consumption	Saba D. et al. [65]	2022	Smart home electricity management	Decision-making tool (IRRHEM)	*Applied Sciences*
Consumption	Zaimen K. et al. [66]	2022	Wireless Sensor Networks	Generic algorithm, particle swarm optimization, flower pollination, and ant colony optimization	*IEEE Access*
Consumption	Serrano W. [67]	2022	Smart Buildings	Neural networks with deep learning structure	*Neural Computing and Applications*
Renewables	Li J. et al. [68]	2022	Hydrogen production and conversion	Fuzzy Methods	*Sustainable Cities and Society*
Renewables	Doosti R. et al. [69]	2022	Industrial Building renewable energy	CPLEX Solver	*IET Smart Cities*
Renewables	Vyas M. et al. [70]	2022	Urban Space Utilization	Use of PV Trees on urban areas	*Renewable Energy*
Renewables	AlHammadi A. et al. [71]	2022	Hybrid renewable systems for vehicle charging	Hybrid Optimization of Multiple Energy Resources	*Energies*
Renewables	Balabel A. et al. [72]	2022	Solar energy in building sectors	Solatube technology analysis	*Alexandria Engineering Journal*
Renewables	Nuvvula R.S.S. et al. [73]	2022	Optimal configuration of PV and wind conversion system	Particle Swarm Optimization	*Sustainable Energy Technologies and Assessments*
Renewables	Ponce P. et al. [74]	2022	Solar/PV Systems	Fuzzy TOPSIS	*Energies*
Generation	Konhäuser W. [75]	2021	Local energy generation	Blockchain Technology (BCT)	*Wireless Personal Communications*
Generation	Pérez-Romero Á. et al. [76]	2021	Operation and Maintenance of PV plants	Five AI-based models	*Applied Sciences*

Table 11. *Cont.*

Area of Application	Author(s)	Year	Category	Method	Source
Generation	Zhou H. et al. [77]	2021	PV energy generation forecasting	Hybrid Deep Learning	*Wireless Communications and Mobile Computing*
Generation	Saini G.S. et al. [78]	2021	Resource Management	Fuzzy Logic	*Recent Advances in Computer Science and Communications*
Transmission	Antonopoulos I. et al. [79]	2021	Smart Grid Smart City (SGSC) project	Energy Demand Response Modeling	*Energy and AI*
Distribution	Wang K. et al. [2]	2021	Decision making in Smart Cities	IoT and Artificial Intelligence	*Sustainability*
Distribution	Calamaro N. et al. [80]	2021	Energy losses detection	Energy fraud detection algorithm	*Sustainability*
Consumption	Manman L. et al. [81]	2021	Energy efficiency	Distributed Artificial Intelligence (DAI)	*Sustainable Cities and Society*
Consumption	Li J. et al. [82]	2021	Decision Support Systems	Internet of Things (IoT)	*Computers and Industrial Engineering*
Consumption	Ghadami N. et al. [10]	2021	Forecast energy consumption	Artificial Neural Network (ANN)	*Sustainable Cities and Society*
Consumption	Cirella G.T. et al. [83]	2021	Smart Electricity	Different AI algorithms	*Energies*
Consumption	Hu Y.-C. et al. [84]	2021	Energy decomposition in smart meter	Neuro-fuzzy classifier	*Processes*
Consumption	Mahmood D. et al. [85]	2021	Energy Management	Demand Side Management (DSM)	*International Journal of Advanced and Applied Sciences*
Consumption	Wang X. et al. [86]	2021	Energy consumption of ac-grid system	Fuzzy Logic	*Journal of Intelligent and Fuzzy Systems*
Generation	Kanase-Patil A.B. et al. [87]	2020	Power generation in Smart City	Different AI algorithms	*Environmental Technology Reviews*
Generation	Serban A.C. and Lytras M.D. [11]	2020	Renewable Energy in Smart Cities	Different AI algorithms	*IEEE Access*
Generation	Jiang Y. et al. [88]	2020	Improvement of Urban Development	IoT	*IEEE Access*
Transmission	Cheng Y. et al. [89]	2020	Demand Forecasting	Neural Network	*IET Smart Cities*
Transmission	Ullah Z. et al. [3]	2020	Energy Efficiency of Smart Grids	Machine learning (ML), Deep Reinforcement Learning	*Computer Communications*
Distribution	Loose N. et al. [90]	2020	Smart grids, energy networks	Unified energy agent	*Sustainability*
Distribution	Fattahi J. et al. [91]	2020	Financial Resources	Distributed Energy Management System (DERMS)	*Sustainable Cities and Society*
Consumption	Sharma S. [92]	2020	Infrastructure	Smart vs Intelligent comparison	*International Journal of Advanced Research in Engineering and Technology*
Consumption	Marinakis V. et al. [93]	2020	Energy consumption reduction	Novel framework with reward schemes	*Sensors*
Consumption	Ullah A. et al. [28]	2020	Energy consumption prediction	Clustering based analysis	*Sensors*
Consumption	Shah A.S. et al. [94]	2020	Energy consumption in smart buildings	Bat algorithm, fuzzy logic	*IEEE Access*
Consumption	Azzaoui A.E. et al. [12]	2020	Energy saving	Blockchain and AI	*IEEE Access*
Consumption	Guo Y. et al. [95]	2020	Minimizing cost of energy consumption	Ant colony optimization (ACO)	*IEEE Access*
Consumption	Zhuang H. et al. [96]	2020	Building energy management	ANN and Fuzzy Logic Controller	*Environmental Modeling and Software*

Table 11. *Cont.*

Area of Application	Author(s)	Year	Category	Method	Source
Renewables	Algieri A. et. al. [97]	2020	Biofuel Rankine Cycle combined with Renewable sources	Multivariable optimization	*Energies*
Renewables	Kumar D. [98]	2020	Urban energy system	Simulation of hybrid urban renewable energy systems	*Energy Exploration and Exploitation*
Generation	Aghajani D. et al. [99]	2019	Wind Turbines Monitoring	Geographic information system and RETSCREEN software	*International Journal of Environmental Science and Technology*
Generation	Oun A. et al. [100]	2019	Energy rationalization of a steel plant	AI, Smart Metering (SM), Automated Decision Making (ADM)	*International Journal of Advanced Computer Science and Applications*
Consumption	Salehi H. et al. [101]	2019	Structural Health Monitoring Energy Consumption	Data mining with pattern recognition, an innovative probabilistic approach, and machine learning	*Expert Systems with Applications*
Consumption	Dong Y. et al. [102]	2019	Energy consumption management	Fairness cooperation algorithm (FCA)	*IEEE Internet of Things Journal*
Consumption	Krayem A. et al. [103]	2019	Energy consumption prediction	Archetypal classification	*Energy and Buildings*
Consumption	Marin-Perez R. et al. [104]	2019	Energy consumption improvement	PLUG-N-HARVEST architecture	*Sensors*
Consumption	Vázquez-Canteli J.R. et al. [30]	2019	Energy saving and demand response	Advanced machine learning algorithms	*Sustainable Cities and Society*
Consumption	Aymen F. and Mahmoudi' C. [105]	2019	Electric Vehicles energy	Support vector classification	*Energies*
Renewables	Khoury D. and Keyrouz F. [106]	2019	Wind and Solar power forecasting	Convolutional Neural Network (CNN)	*WSEAS Transactions on Power Systems*
Consumption	Alhussein M. et al. [107]	2019	Microgrid energy management	Deep learning model	*Energies*
Consumption	Risso C. [108]	2019	Energy demand control	Combinatorial optimization dispatch models	*Revista Facultad de Ingeniería*
Generation	Njuguna Matheri A. et al. [109]	2018	Waste quantification for biofuel	Simple Multi Attribute Rating (SMART) of Multiple Criteria Decision Analysis (MCDA)	*Renewable and Sustainable Energy Reviews*
Transmission	Serrano W. [4]	2018	Digital Systems, Transmission Networks	Digital as a Service (DaaS), IoT, Blockchain, Virtual Reality	*Smart Cities*
Consumption	Chui K.T. et al. [110]	2018	Electricity consumption	Hybrid genetic algorithm support vector machine kernel learning approach (GA-SVM-MKL)	*Energies*
Consumption	Rahman A. et al. [27]	2018	Medium-long term energy predictions	Recurrent Neural Network (RNN)	*Applied Energy*
Renewables	Ramli M.A.M. et al. [27]	2018	Microgrid Systems	Multi-Objective Self-Adaptive Different Evolution (MOSaDE) algorithm	*Renewable Energy*
Renewables	Ashfaq A. and Ianakiev A. [111]	2018	Technical and cost design to decarbonize the heating network	Large Scale heat pump and thermal heat storage	*Energy*
Generation	Laiola E. and Giungato P. [112]	2018	Wind characterization	Statistical methods used for meteorological and economic data	*Journal of Cleaner Production*
Renewables	Oldebroek V. et al. [17]	2017	Fully Renewable integrated transport	An energy balance and cost analysis	*International Journal of Hydrogen Energy*

Table 11. *Cont.*

Area of Application	Author(s)	Year	Category	Method	Source
Transmission	Rekik M. et al. [113]	2016	Smart Grid	Ant Colony Optimization (ACO)	*Sustainable Cities and Society*
Consumption	De Paz J.F. et al. [114]	2016	Optimization of energy consumption and cost	Artificial neural networks (ANN), multi-agent systems (MAS)	*Information Sciences*
Consumption	Peña M. et al. [115]	2016	Energy inefficiencies detection in smart buildings.	Data mining	*Expert Systems with Applications*
Consumption	Huang J. et al. [116]	2016	Energy consumption of train	Decision tree, data mining	*IEEE Transactions on Computers*
Consumption	Sędziwy A. and Kotulski L. [117]	2016	Lighting system energy consumption	Dynamic street lighting control	*Energies*
Transmission	Lützenberger M. et al. [118]	2015	Energy in Smart Cities	Distributed Artificial Intelligence Laboratory	*Journal of Ambient Intelligence and Humanized Computing*
Consumption	Fernández C. et al. [119]	2014	Energy consumption modeling	Automated vacuum waste collection (AVWC)	*Sustainability*
Consumption	Yang D. et al. [16]	2013	Solar irradiance forecasting	Time-Forward kriging	*Renewable Energy*
Generation	Park C.J. et al. [120]	2013	Forecasting of renewable energy	Spatio-Temporal correlation	*International Journal of Multimedia and Ubiquitous Engineering*

4.1. Energy Generation

The Scopus search yielded a total of 46 articles as a result of the initial exploration. After filtering the search to focus solely on articles with a primary emphasis on energy generation, a total of 17 articles were identified that met all eligibility criteria and were not duplicated in other sections. These 17 articles will form the basis of our analysis and in-depth examination of the advancements and research trends related to energy generation in the context of AI applications in Smart Cities.

For the renewable energy section, a total of 48 articles were obtained, but after filtering these articles, choosing just the ones that were mostly related to renewable energy generation in Smart Cities, a total of 24 articles were obtained. These articles are added to the energy generation section in order to have a more complete review.

Energy generation forecasting, particularly of alternative sources, emerged as one of the main topics identified in this section. The selected articles delve into the application of AI methodologies for predicting energy generation from renewable and sustainable sources. This area of research is of significant importance in the context of Smart Cities, as it contributes to enhancing the integration and utilization of alternative energy sources to meet the growing energy demands sustainably. The analysis of these articles will provide valuable insights into the advancements and challenges in accurately forecasting energy generation from renewable sources, enabling better energy planning and management in Smart City environments. In [31], the authors developed a method based on non-parametric regression models that forecasts the demand and generation of energy with information provided by smart meters. Another application for forecasting purposes can be reviewed in [33], where a physics-informed AI is applied that forecasts wind power generation, with information on a wind farm in China and ML methods. Reference [45] shows an extensive review of Fuzzy Hybrid Methods, future possible challenges, and opportunities in this sector. This study shows that combining fuzzy logic systems can enhance the efficiency of solar energy applications, and the approach outlined in this research can be applied to investigate various renewable energy sources.

Another application found was the Maximum PowerPoint Tracking of photovoltaic panels, which is the point where solar PV panels produce the maximum energy possible, and the tracking of this point increases their energy efficiency; in [50], a Finite-Time Terminal Attractor (FFTA) is combined with Gradient Particle Swarm Optimization (GPSO) to track MPPT of a solar PV system. Another application in solar energy can be found in [10], in which an Artificial Neural Network (ANN) is applied to create a decision-making tool based on the generation and consumption of solar PV systems that can aid decision makers in creating strategies towards energy generation; these strategies include reducing costs and/or maximizing solar energy generation.

Hence, a trend that can be noticed is that AI has been applied for energy generation forecasting and also to increase the energy efficiency from PV systems, which increases the power generation. AI helps to manage large amounts of data to predict these forecasting models and also manages generation data to track the MPPT for PV panels. In addition, AI has been applied in decision-making tools that consider generation and consumption to provide alternatives that can bring benefits in terms of economic and energy efficiency.

In addition, the study presented in [121] primarily concentrates on employing fuzzy decision-making tools in supply chain management rather than tackling energy issues directly. The paper mainly emphasizes developing and applying dynamic spherical fuzzy aggregation operators (AOs) for multi-period decision making (MPDM) within supply chain management. This concentration differs significantly from typical areas of interest in energy-related studies in Smart Cities, which generally include energy generation, distribution, consumption, efficiency, renewable sources, and sustainable energy practices. Furthermore, the technical approach, involving mathematical models and algorithms for decision making, is designed to manage uncertainty and imprecision in these processes. Although these methodologies benefit their respective fields, they do not contribute directly to advancing energy systems or technologies in Smart Cities, particularly those utilizing AI in the energy sector. The case studies and examples provided in the paper focus on supply chain management, an essential aspect of urban systems. However, they do not cover critical elements of energy management in Smart Cities, such as energy generation, conservation, or optimization strategies, often involving smart grids and the integration of renewable energy.

The paper [122] shows a unique approach, focusing on and contributing to energy management and sustainability. It searches the expansion of renewable energy, exploring its applications and open research problems. It emphasizes the evolution, theoretical underpinnings, and practical applications of various renewable energy sources, including solar, wind, bioenergy, hydraulic energy, and waste-to-energy conversions. Conducting an extensive literature review, it covers developments from 2010 to 2022 and proposes innovative ideas and cost-effective models for implementing renewable energy across different sectors.

In contrast, this review paper is oriented towards integrating Artificial Intelligence (AI) in the energy sector within Smart Cities. It employs the PRISMA methodology and the Scopus database to review the literature, systematically analyzing 122 peer-reviewed articles. This review underscores the pivotal role of AI technologies in improving urban energy processes across four key domains: generation, transmission, distribution, and consumption. It identifies trends, high-impact articles, and emerging keyword clusters, providing a comprehensive analytical framework on the multifaceted applications of AI in the energy sectors of Smart Cities.

While the study in [122] is aimed primarily at researchers and practitioners in the field of renewable energy, offering innovative solutions and pinpointing open areas for future research, this review paper is geared towards policymakers, urban planners, and researchers. It emphasizes the use of AI to achieve sustainable and efficient energy management in Smart Cities. Although both articles contribute to the larger conversation on energy management and sustainability, they have distinct focal points: [122] centers on the various applications of renewable energy, while this review paper focuses on the transformative impact of AI in managing energy resources in the context of Smart Cities.

4.2. Energy Transmission

After conducting a thorough search using the method described above, a total of 31 articles were obtained for this section. The filters applied considered both energy and transmission; however, it is worth noting that some of the results were centered on IoT networks and data transmission (not energy transmission). To ensure precision, only articles that focused on energy transmission in their abstract were considered, resulting in a total of 10 relevant articles.

In [34], the authors elaborate on various concepts related to energy transmission lines in Smart Cities, particularly with the introduction of smart grids. Smart grids are advanced systems that integrate automation, data transmission, and energy monitoring at each stage of the energy supply chain, from generation to final consumption. This integration facilitates seamless communication and coordination between different components of the energy transmission network within a Smart City. This paper emphasizes that concepts such as the Internet of Things (IoT) and cloud computing play a vital role in enhancing energy transmission. These technologies enable efficient data management, as they can handle vast amounts of information exchanged between various energy transmission networks within a Smart City. By leveraging IoT and cloud computing, smart grids optimize the management and distribution of energy resources, contributing to the achievement of Smart Cities' objectives. The implementation of smart grids in energy transmission is pivotal for effectively carrying energy from its source to the end-users consumption. The integration of these advanced systems enables greater energy efficiency, sustainability, and alignment with the goals of Smart City development. Smart grids integration is also mentioned in [3,52,79], so there is a close connection between smart grids and energy transmission for AI applications in Smart Cities.

In [89], it is stated that in order to have an appropriate electric transmission, an anomaly detection system is required to avoid power losses. In this article, an AI method called PowerNet, which is based on neural networks, is proposed to detect anomalies for electricity theft detection in the smart grids, so the AI could make a contribution to automatically detect these problems and report them. Even though the main contribution of this article is regarding energy forecasting, the proposed AI method is explored in this article, and its application for transmission is reviewed.

The work presented in [48] mentions several methodologies for the demand side management (DSM) application in power grids, which is again mentioned for energy transmission and the application of IOT, but also introduces the SM, which is a mixture between software and hardware that helps to give real-time data, with valuable precision, about the energy consumption, which can be useful for monitoring purposes and home area networks (HANs), which are utilized to connect electric devices at home.

4.3. Energy Distribution

Using the methodology this time for *Energy Distribution*, a total of 21 relevant articles were obtained. Among these, some discussed the heating load in buildings, some others focused on electric vehicles, which briefly mentioned the Smart City concept. To narrow down the selection of the articles, the criterion used was to include articles whose abstract prominently features energy distribution as one of the main topics. Upon careful review, it was found that only four papers either focused solely on energy distribution or made significant contributions in this area. These selected articles will be subject to a thorough examination to identify their key findings, contributions, and emerging trends in the field of energy distribution within Smart Cities. Although the number of articles in this category may be relatively small, their significance lies in the valuable insights they provide regarding energy distribution strategies and advancements in the context of smart cities.

The work presented in [2] shows Artificial Neural Networks (ANNs) and machine learning algorithms like Support Vector Machine (SVM) to train energy prediction models that could contribute to obtaining the amount of energy consumption of buildings in Smart Cities, helping distribution systems to be more efficient.

From the literature review, in [90], a multi-agent-based simulation of the distribution networks of a city in Germany reached the objective of the article of successfully simulating the dynamic model of the city energy network, and this simulation was compared to professional simulation tools, which had a relative error lower than 0.0000084%. Another important approach to the application of AI in energy distribution is present in [80], which explains the development of an algorithm to solve energy fraud detection to minimize energy loss in the electricity grid. This algorithm used Convolutional Neural Networks (CNNs) and Robotic Process Automation (RPA) to detect precise fraud identification in electricity networks, the main objective of which was to separate electricity fraud from the many other anomalies that could be presented in the network. The last article reviewed in this section is the work presented in [91], which is considered an energy internet architecture to reach an economic mechanism for clean energy management. This work is not completely focused on an energy distribution approach, but the work could contribute to clean energy integration, which is an important part of Smart Cities. Indeed, a noticeable trend can be observed in the area of energy distribution. This trend revolves around three key aspects: simulating distribution networks, detecting faults in distribution networks, and predicting energy.

4.4. Energy Consumption

The search conducted for the base terms followed by energy consumption resulted in a total of 103 articles. After the screening, 49 articles of this set fulfilled the eligibility criteria, and said articles are listed in Table 11 under *Consumption* Area of Application. Common topics among the reviewed articles were forecasting, data mining, economy, energy management, user profiling, behavior modeling, electric vehicles, and computing.

A paper that alludes to forecasting found during this research is [35], which proposes a smart meter time series from generation sources, the electric grid, and localized buildings to attain a *Digital Twin* of the entire system with the added benefit of allowing geospatial information to be fed to the *twin*. The results show that when geospatial data are not available, a 7% overestimation of the grid level is performed during the summer days. A different approach to forecasting the energy consumption of individual residential households is the one proposed in [89]; this case study presents a neural network architecture named PowerNet, which can incorporate historical supply and demand, weather data, and date information to forecast energy consumption. Some of the machine learning algorithms used by *PowerNet* are Gradient Boosting Tree (GBT), Support Vector Regression (SVR), Random Forest (RF), and Gated Recurrent Unit (GRU). Additionally, PowerNet can also be used for anomaly detection in power systems. The use of Recurrent Neural Networks is proposed in [27] to forecast the consumption of commercial and residential buildings in medium- to long-term time horizons (greater than a week). The model proposed in this article demonstrates the capability to predict unknown transient responses, making it promising for forecasting hourly electricity consumption as well. In [74], the Fuzzy-TOPSIS decision-making method is used to evaluate the selection of Mexican manufacturing companies for installing solar panels. Additionally, the S4 framework is implemented to improve the decision-making process by Fuzzy-TOPSIS.

One of the articles that focuses on building energy management to minimize power consumption is [67], This paper examines the application of deep learning structures. Initially, sensory neurons are spread throughout the smart building, collecting data from the environment. Subsequently, a reinforcement learning algorithm is employed to predict values and trends, thereby aiding the building managers with the decision-making task. The proposal called *iBuilding* is validated using a public research data set, demonstrating that Artificial Intelligence within smart buildings allows the real-time monitoring and accurate predictions of its variables.

Previously mentioned examples show a growing trend of the use of AI in the forecasting of the energy consumption sector due to the availability of more information on weather conditions and domestic appliances' energy consumption. It is possible to use the data gathered to train neural networks and models to have more precision. The historical patterns can be studied.

4.5. Research Gaps

As detailed in this literature review, AI applications in the energy sector reveal the current state of research and uncover several technological gaps that present opportunities for future innovation. The role of AI in forecasting alternative sources like wind and solar is well established in energy generation. However, a technological gap remains in the accurate energy output prediction under varying environmental conditions. Additionally, while AI has made strides in the operation and monitoring of these sources, there is a need for more advanced AI systems that can dynamically adapt to changing energy demands and integrate seamlessly with traditional energy grids. This gap is particularly evident in the context of hybrid energy systems in Smart Cities, where a diverse array of energy sources must be efficiently managed. In transmission and distribution, AI has significantly contributed to smart grid management and energy loss detection. However, a notable gap exists between the long-distance transmission efficiency and the integration of distributed energy resources. Current AI models often struggle with the complexity of large-scale, interconnected networks. There is a need for more sophisticated AI algorithms capable of optimizing energy flow across massive and varied geographical areas. On the consumption side, AI has been instrumental in reducing energy usage, forecasting demand, and managing building energy systems. Yet, a technological gap is evident in personalizing energy consumption strategies. AI systems that can learn and adapt to individual user behaviors and preferences in real time are in progress. Such systems could significantly enhance energy efficiency at the consumer level. While AI applications in forecasting and EV charging are advancing in the renewable energy sector, there is a gap in the comprehensive integration of various renewable sources. Research heavily focuses on solar, wind, and hydrogen, but other sources like hydropower, geothermal, and bio-energy are less explored. AI applications in these areas are not as developed, indicating a gap in diversifying renewable energy sources within Smart Cities. In addition, integrating AI systems is a cross-cutting technological gap across all these sectors. Figure 17 shows a brief description in this section. While AI is being applied in siloed aspects of the energy sector, there is a lack of holistic, interconnected AI frameworks that can manage the energy life-cycle from generation to consumption in a unified manner. Such integration is crucial for the development of truly smart, efficient cities. Finally, while AI has made significant inroads in the energy sector, our review highlights several technological gaps. Addressing these gaps requires focused research and development efforts, aiming for more sophisticated, adaptable, and integrated AI solutions that can meet the complex demands of modern energy systems, particularly in the context of Smart Cities.

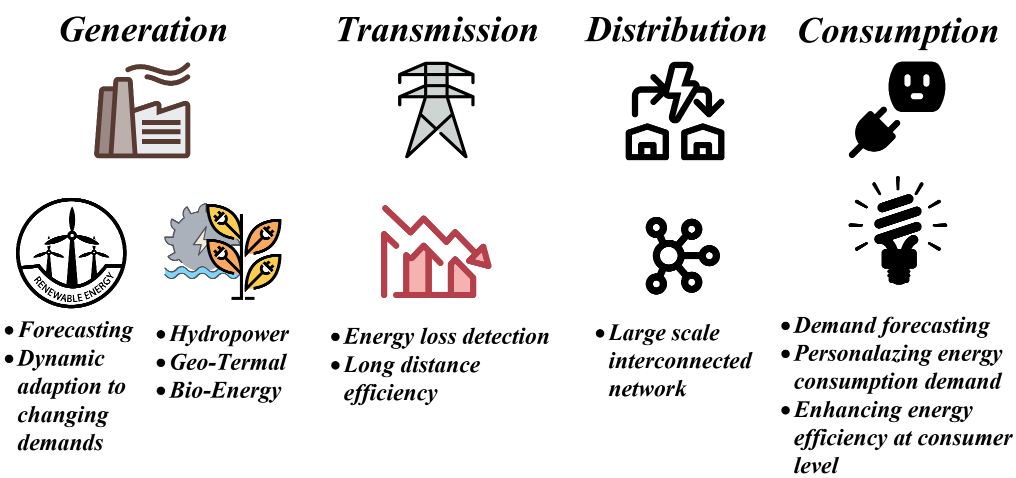

Figure 17. Illustrative description on research gaps section.

5. Conclusions

This paper contributes to understanding the integration and application of Artificial Intelligence (AI) within the energy sector, especially in Smart Cities. The study systematically delineates the existing literature into four key domains, energy generation, transmission, distribution, and consumption, meticulously reviewing a compendium of 122 articles sourced from Scopus. A salient feature of this paper is its temporal analysis, revealing an exponential surge in publication growth over the years. In energy generation alone, publications have increased from a single article in 2016 to 45 in 2023, representing a staggering annual growth rate of 42.62 percent. Comparable ascendant trajectories are discerned in other domains, such as energy transmission and distribution. Furthermore, the paper sheds light on renewable energy, focusing on the integration of solar and wind energy in Smart Cities, outlined in the Energy Generation section. A crucial aspect of this research lies in keyword co-occurrence analysis, enabling the identification of predominant AI techniques in current practice. Concepts such as artificial intelligence, economics, energy efficiency, data analytics, renewable energy, and deep learning have emerged as integral to the formulation of intelligent energy solutions. This comprehensive analysis provides a robust framework for deciphering the multifarious AI techniques and their application. From machine learning algorithms, such as Ant Colony Optimization and neural networks, to the nascent trends in smart grids, these innovations are pivotal in spearheading advancements in energy forecasting, consumption prediction, and intelligent control systems. The aim of this paper is to present a profound and up-to-the-minute overview of the influential role of AI in the energy sector of Smart Cities. It meticulously tracks the evolution and impact of research in this field and pinpoints the foremost technologies and methodologies expected to shape forthcoming innovations. This paper serves as a repository of information on current trends and a compass pointing toward the future trajectories in AI-mediated intelligent energy solutions within the progressive ecosystems of Smart Cities.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ACO	Ant Colony Optimization
ADM	Automatic Decision Making
AIA	Artificial Intelligence Analytics
AIMS-SB	Artificial Intelligence Technique for Monitoring Systems in Smart Buildings
ANN	Artificial Neural Network
AVWC	Automated Vacuum Waste Collection
BCT	Blockchain Technology
BiKSTM	Bidirectional Long Short-Term Memory
CNN	Convolutional Neural Network

DaaS	Device as a Service
DAI	Distributed Artificial Intelligence
DCESN	Deep-Chain Echo State Network
DCNN	Dilated Convolutional Neural Network
DERMS	Distributed Energy Management System
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DSM	Demand Side Management
FCA	Fairness Cooperation Algorithm
FFTA	Finite-Time Terminal Attractor
GA	Genetic Algorithm
GHG	Greenhouse gas
GPSO	Gradient Particle Swarm Optimization
IGWO	Improved Gray Wolf Optimization
IOT	Internet of Things
IPTO	Improved Phase Timing Optimization
LSTM	Long Short-Term Memory
MAS	Multi Agent Systems
MCDA	Multiple Criteria Decision Analysis
MKL	Machine Kernel Learning
ML	Machine Learning
MPPT	Maximum Power Point Tracking
PV	Photovoltaic
QRL	Quantum-Inspired Reinforcement Learning
RNN	Recurrent Neural Network
SAE	Stacked Autoencoder
SM	Smart Metering
SMART	Simple Multi-Attribute Rating
SVM	Support Vector Machine
XELF	Explainable Electrical Load Forecasting

References

1. Llanez-Caballero, I.; Ibarra, L.; Peña-Quintal, A.; Catzín-Contreras, G.; Ponce, P.; Molina, A.; Ramirez-Mendoza, R. The "Smart" concept from an electrical sustainability viewpoint. *Energies* **2023**, *16*, 3072. [CrossRef]
2. Wang, K.; Zhao, Y.; Gangadhari, R.K.; Li, Z. Analyzing the adoption challenges of the Internet of things (Iot) and artificial intelligence (ai) for smart cities in china. *Sustainability* **2021**, *13*, 10983. [CrossRef]
3. Ullah, Z.; Al-Turjman, F.; Mostarda, L.; Gagliardi, R. Applications of artificial intelligence and machine learning in smart cities. *Comput. Commun.* **2020**, *154*, 313–323. [CrossRef]
4. Serrano, W. Digital systems in smart city and infrastructure: Digital as a service. *Smart Cities* **2018**, *1*, 134–154. [CrossRef]
5. Moghaddam, S.M.S.H.; Dashtdar, M.; Jafari, H. AI applications in smart cities' energy systems automation. *Repa Proc. Ser.* **2022**, *3*, 1–5. [CrossRef]
6. Mehmood, M.U.; Chun, D.; Han, H.; Jeon, G.; Chen, K. A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment. *Energy Build.* **2019**, *202*, 109383. [CrossRef]
7. Ahmad, T.; Zhu, H.; Zhang, D.; Tariq, R.; Bassam, A.; Ullah, F.; AlGhamdi, A.S.; Alshamrani, S.S. Energetics Systems and artificial intelligence: Applications of industry 4.0. *Energy Rep.* **2022**, *8*, 334–361. [CrossRef]
8. Li, G.; Jin, Y.; Akram, M.; Chen, X.; Ji, J. Application of bio-inspired algorithms in maximum power point tracking for PV systems under partial shading conditions—A review. *Renew. Sustain. Energy Rev.* **2018**, *81*, 840–873. [CrossRef]
9. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. Declaración PRISMA 2020: Una guía actualizada para la publicación de revisiones sistemáticas. *Rev. Espa Nola De Cardiol.* **2021**, *74*, 790–799. [CrossRef]
10. Ghadami, N.; Gheibi, M.; Kian, Z.; Faramarz, M.G.; Naghedi, R.; Eftekhari, M.; Fathollahi-Fard, A.M.; Dulebenets, M.A.; Tian, G. Implementation of solar energy in smart cities using an integration of artificial neural network, photovoltaic system and classical Delphi methods. *Sustain. Cities Soc.* **2021**, *74*, 103149. [CrossRef]
11. Serban, A.C.; Lytras, M.D. Artificial intelligence for smart renewable energy sector in europe—Smart energy infrastructures for next generation smart cities. *IEEE Access* **2020**, *8*, 77364–77377. [CrossRef]
12. Azzaoui, A.E.; Singh, S.K.; Pan, Y.; Park, J.H. Block5GIntell: Blockchain for AI-Enabled 5G Networks. *IEEE Access* **2020**, *8*, 145918–145935. [CrossRef]
13. Lee, Y.L.; Qin, D.; Wang, L.C.; Sim, G.H. 6G Massive Radio Access Networks: Key Applications, Requirements and Challenges. *IEEE Open J. Veh. Technol.* **2021**, *2*, 54–66. [CrossRef]

14. Zhang, N.; Chen, H.; Chen, X.; Chen, J. Semantic framework of internet of things for smart cities: Case studies. *Sensors* **2016**, *16*, 1501. [CrossRef] [PubMed]
15. Ramli, M.A.; Bouchekara, H.; Alghamdi, A.S. Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm. *Renew. Energy* **2018**, *121*, 400–411. [CrossRef]
16. Yang, D.; Gu, C.; Dong, Z.; Jirutitijaroen, P.; Chen, N.; Walsh, W.M. Solar irradiance forecasting using spatial-temporal covariance structures and time-forward kriging. *Renew. Energy* **2013**, *60*, 235–245. [CrossRef]
17. Oldenbroek, V.; Verhoef, L.A.; van Wijk, A.J. Fuel cell electric vehicle as a power plant: Fully renewable integrated transport and energy system design and analysis for smart city areas. *Int. J. Hydrogen Energy* **2017**, *42*, 8166–8196. [CrossRef]
18. De Luca, G.; Fabozzi, S.; Massarotti, N.; Vanoli, L. A renewable energy system for a nearly zero greenhouse city: Case study of a small city in southern Italy. *Energy* **2018**, *143*, 347–362. [CrossRef]
19. Aguilar, J.; Garces-Jimenez, A.; R-moreno, M.; García, R. A systematic literature review on the use of artificial intelligence in energy self-management in smart buildings. *Renew. Sustain. Energy Rev.* **2021**, *151*, 111530. [CrossRef]
20. Sharma, H.; Haque, A.; Blaabjerg, F. Machine learning in wireless sensor networks for smart cities: A survey. *Electronics* **2021**, *10*, 1012. [CrossRef]
21. Khan, N.; Haq, I.U.; Khan, S.U.; Rho, S.; Lee, M.Y.; Baik, S.W. DB-Net: A novel dilated CNN based multi-step forecasting model for power consumption in integrated local energy systems. *Int. J. Electr. Power Energy Syst.* **2021**, *133*, 107023. [CrossRef]
22. Le, L.T.; Nguyen, H.; Dou, J.; Zhou, J. A comparative study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in estimating the heating load of buildings' energy efficiency for smart city planning. *Appl. Sci.* **2019**, *9*, 2630. [CrossRef]
23. Idowu, S.; Saguna, S.; Åhlund, C.; Schelén, O. Applied machine learning: Forecasting heat load in district heating system. *Energy Build.* **2016**, *133*, 478–488. [CrossRef]
24. Zhou, Z.; Wang, B.; Guo, Y.; Zhang, Y. Blockchain and computational intelligence inspired incentive-compatible demand response in internet of electric vehicles. *IEEE Trans. Emerg. Top. Comput. Intell.* **2019**, *3*, 205–216. [CrossRef]
25. Le, L.T.; Nguyen, H.; Zhou, J.; Dou, J.; Moayedi, H. Estimating the heating load of buildings for smart city planning using a novel artificial intelligence technique PSO-XGBoost. *Appl. Sci.* **2019**, *9*, 2714. [CrossRef]
26. Ingwersen, P.; Serrano-López, A.E. Smart city research 1990–2016. *Scientometrics* **2018**, *117*, 1205–1236. [CrossRef]
27. Rahman, A.; Srikumar, V.; Smith, A.D. Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. *Appl. Energy* **2018**, *212*, 372–385. [CrossRef]
28. Ullah, A.; Haydarov, K.; Haq, I.U.; Muhammad, K.; Rho, S.; Lee, M.; Baik, S.W. Deep learning assisted buildings energy consumption profiling using smart meter data. *Sensors* **2020**, *20*, 873. [CrossRef]
29. Alsamhi, S.H.; Ma, O.; Ansari, M.S.; Almalki, F.A. Survey on collaborative smart drones and internet of things for improving smartness of smart cities. *IEEE Access* **2019**, *7*, 128125–128152. [CrossRef]
30. Vázquez-Canteli, J.R.; Ulyanin, S.; Kämpf, J.; Nagy, Z. Fusing TensorFlow with building energy simulation for intelligent energy management in smart cities. *Sustain. Cities Soc.* **2019**, *45*, 243–257. [CrossRef]
31. Miyasawa, A.; Akira, S.; Fujimoto, Y.; Hayashi, Y. Forecast of area-scale behaviours of behind-the-metre solar power and load based on smart-metering net demand data. *IET Smart Cities* **2023**, *5*, 19–34. [CrossRef]
32. Shafiullah, M.; Rahman, S.; Imteyaz, B.; Aroua, M.K.; Hossain, M.I.; Rahman, S.M. Review of Smart City Energy Modeling in Southeast Asia. *Smart Cities* **2023**, *6*, 72–99. [CrossRef]
33. Wu, Z.; Sun, B.; Feng, Q.; Wang, Z.; Pan, J. Physics-Informed AI Surrogates for Day-Ahead Wind Power Probabilistic Forecasting with Incomplete Data for Smart Grid in Smart Cities. *CMES Comput. Model. Eng. Sci.* **2023**, *137*, 527–554. [CrossRef]
34. Fakhar, A.; Haidar, A.M.; Abdullah, M.; Das, N. Smart grid mechanism for green energy management: A comprehensive review. *Int. J. Green Energy* **2023**, *20*, 284–308. [CrossRef]
35. Bayer, D.; Pruckner, M. A digital twin of a local energy system based on real smart meter data. *Energy Inform.* **2023**, *6*, 8. [CrossRef]
36. Alymani, M.; Mengash, H.A.; Aljebreen, M.; Alasmari, N.; Allafi, R.; Alshahrani, H.; Elfaki, M.A.; Hamza, M.A.; Abdelmageed, A.A. Sustainable residential building energy consumption forecasting for smart cities using optimal weighted voting ensemble learning. *Sustain. Energy Technol. Assess.* **2023**, *57*, 103271. [CrossRef]
37. Al-Habaibeh, A.; Yaseen, S.; Nweke, B. A comparative study of low and high resolution infrared cameras for IoT smart city applications: A comparative study of low and high resolution infrared cameras. *Ain Shams Eng. J.* **2023**, *14*, 102108. [CrossRef]
38. Selvaraj, R.; Kuthadi, V.M.; Baskar, S. Smart building energy management and monitoring system based on artificial intelligence in smart city. *Sustain. Energy Technol. Assess.* **2023**, *56*, 103271. [CrossRef]
39. Feng, Y.; Huang, Y.; Li, B.; Peng, H.; Wang, J.; Zhou, W. Connectivity Enhancement of E-VANET Based on QL-mRSU Self-Learning Energy-Saving Algorithm. *IEEE Access* **2023**, *11*, 3810–3825. [CrossRef]
40. Jiang, R.; Zeng, S.; Song, Q.; Wu, Z. Deep-Chain Echo State Network With Explainable Temporal Dependence for Complex Building Energy Prediction. *IEEE Trans. Ind. Inform.* **2023**, *19*, 426–435. [CrossRef]
41. AlHajri, I.; Ahmadian, A.; Alazmi, R. A comprehensive technical, economic, and environmental evaluation for optimal planning of renewable energy resources to supply water desalination units: Kuwait case study. *Energy* **2023**, *275*, 127416. [CrossRef]
42. Fantin Irudaya Raj, E.; Appadurai, M.; Lurthu Pushparaj, T.; Chithambara Thanu, M. Wind turbines with aramid fiber composite wind blades for smart cities like urban environments: Numerical simulation study. *MRS Energy Sustain.* **2023**, *10*, 139–156. [CrossRef]

43. Khan, N.; Khan, S.U.; Ullah, F.U.M.; Lee, M.Y.; Baik, S.W. AI-Assisted Hybrid Appr Approach for Energy Management in IoT-based Smart Microgrid. *IEEE Internet Things J.* **2023**, *10*, 18861–18875. [CrossRef]
44. Ulpiani, G.; Vetters, N.; Shtjefni, D.; Kakoulaki, G.; Taylor, N. Let's hear it from the cities: On the role of renewable energy in reaching climate neutrality in urban Europe. *Renew. Sustain. Energy Rev.* **2023**, *183*, 113444. [CrossRef]
45. Kedir, N.; Nguyen, P.H.; Pérez, C.; Ponce, P.; Fayek, A.R. Systematic Literature Review on Fuzzy Hybrid Methods in Photovoltaic Solar Energy: Opportunities, Challenges, and Guidance for Implementation. *Energies* **2023**, *16*, 3795. [CrossRef]
46. Icaza-Alvarez, D.; Jurado, F.; Tostado-Véliz, M. Long-term planning for the integration of electric mobility with 100 renewable energy generation under various degrees of decentralization: Case study Cuenca, Ecuador. *Energy Rep.* **2023**, *9*, 4816–4829. [CrossRef]
47. Moon, J.; Rho, S.; Baik, S.W. Toward explainable electrical load forecasting of buildings: A comparative study of tree-based ensemble methods with Shapley values. *Sustain. Energy Technol. Assess.* **2022**, *54*, 102888. [CrossRef]
48. Said, D. A Survey on Information Communication Technologies in Modern Demand-Side Management for Smart Grids: Challenges, Solutions, and Opportunities. *IEEE Eng. Manag. Rev.* **2023**, *51*, 76–107. [CrossRef]
49. Heidari, A.; Navimipour, N.J.; Unal, M. Applications of ML/DL in the management of smart cities and societies based on new trends in information technologies: A systematic literature review. *Sustain. Cities Soc.* **2022**, *85*, 104089. [CrossRef]
50. Chang, E.C.; Cheng, C.A.; Wu, R.C. Artificial Intelligence of Things-Based Optimal Finite-Time Terminal Attractor and Its Application to Maximum Power Point Tracking of Photovoltaic Arrays in Smart Cities. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 4213217. [CrossRef]
51. 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]
52. 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.
53. Chavhan, S.; Gupta, D.; Gochhayat, S.P.; Chandana, B.; Khanna, A.; Shankar, K.; Rodrigues, J.J.P.C. Edge Computing AI-IoT Integrated Energy-efficient Intelligent Transportation System for Smart Cities. *ACM Trans. Internet Technol.* **2022**, *22*, 4213217. [CrossRef]
54. Al-Hawawreh, M.; Elgendi, I.; Munasinghe, K. An Online Model to Minimize Energy Consumption of IoT Sensors in Smart Cities. *IEEE Sens. J.* **2022**, *22*, 19524–19532. [CrossRef]
55. Singh, S.; Nikolovski, S.; Chakrabarti, P. GWLBC: Gray Wolf Optimization Based Load Balanced Clustering for Sustainable WSNs in Smart City Environment. *Sensors* **2022**, *22*, 7113. [CrossRef] [PubMed]
56. Huang, J.; Algahtani, M.; Kaewunruen, S. Energy Forecasting in a Public Building: A Benchmarking Analysis on Long Short-Term Memory (LSTM), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost) Networks. *Appl. Sci.* **2022**, *12*, 9788. [CrossRef]
57. Mohamed, H.; Al-Masri, E.; Kotevska, O.; Souri, A. A Multi-Objective Approach for Optimizing Edge-Based Resource Allocation Using TOPSIS. *Electronics* **2022**, *11*, 2888. [CrossRef]
58. Ren, Y.; Xie, R.; Yu, F.R.; Huang, T.; Liu, Y. Green Intelligence Networking for Connected and Autonomous Vehicles in Smart Cities. *IEEE Trans. Green Commun. Netw.* **2022**, *6*, 1591–1603. [CrossRef]
59. Murthy Nimmagadda, S.; Harish, K.S. Review paper on technology adoption and sustainability in India towards smart cities. *Multimed. Tools Appl.* **2022**, *81*, 27217–27245. [CrossRef]
60. Islam, N.; Haseeb, K.; Ali, M.; Jeon, G. Secured Protocol with Collaborative IoT-Enabled Sustainable Communication Using Artificial Intelligence Technique. *Sustainability* **2022**, *14*, 8919. [CrossRef]
61. Zamponi, M.E.; Barbierato, E. The Dual Role of Artificial Intelligence in Developing Smart Cities. *Smart Cities* **2022**, *5*, 728–755. [CrossRef]
62. Naveed, Q.N.; Alqahtani, H.; Khan, R.U.; Almakdi, S.; Alshehri, M.; Rasheed, M.A.A. An Intelligent Traffic Surveillance System Using Integrated Wireless Sensor Network and Improved Phase Timing Optimization. *Sensors* **2022**, *22*, 3333. [CrossRef] [PubMed]
63. Akkad, M.Z.; Haidar, S.; Bányai, T. Design of Cyber-Physical Waste Management Systems Focusing on Energy Efficiency and Sustainability. *Designs* **2022**, *6*, 39. [CrossRef]
64. Garlik, B. Energy Centers in a Smart City as a Platform for the Application of Artificial Intelligence and the Internet of Things. *Appl. Sci.* **2022**, *12*, 3386. [CrossRef]
65. Saba, D.; Cheikhrouhou, O.; Alhakami, W.; Sahli, Y.; Hadidi, A.; Hamam, H. Intelligent Reasoning Rules for Home Energy Management (IRRHEM): Algeria Case Study. *Appl. Sci.* **2022**, *12*, 1861. [CrossRef]
66. Zaimen, K.; Brahmia, M.E.A.; Moalic, L.; Abouaissa, A.; Idoumghar, L. A Survey of Artificial Intelligence Based WSNs Deployment Techniques and Related Objectives Modeling. *IEEE Access* **2022**, *10*, 113294–113329. [CrossRef]
67. Serrano, W. iBuilding: Artificial intelligence in intelligent buildings. *Neural Comput. Appl.* **2022**, *34*, 875–897. [CrossRef]
68. Li, J.; Chen, J.; Yuan, Z.; Xu, L.; Zhang, Y.; Al-Bahrani, M. Multi-objective risk-constrained optimal performance of hydrogen-based multi energy systems for future sustainable societies. *Sustain. Cities Soc.* **2022**, *87*, 104176. [CrossRef]
69. Doosti, R.; Sedighizadeh, M.; Sedighizadeh, D.; Sheikhi Fini, A. Robust stochastic optimal operation of an industrial building including plug in electric vehicle, solar-powered compressed air energy storage and ice storage conditioner: A case study in the city of Kaveh, Iran. *IET Smart Cities* **2022**, *4*, 56–77. [CrossRef]
70. Vyas, M.; Chowdhury, S.; Verma, A.; Jain, V. Solar Photovoltaic Tree: Urban PV power plants to increase power to land occupancy ratio. *Renew. Energy* **2022**, *190*, 283–293. [CrossRef]

71. AlHammadi, A.; Al-Saif, N.; Al-Sumaiti, A.S.; Marzband, M.; Alsumaiti, T.; Heydarian-Forushani, E. Techno-Economic Analysis of Hybrid Renewable Energy Systems Designed for Electric Vehicle Charging: A Case Study from the United Arab Emirates. *Energies* **2022**, *15*, 6621. [CrossRef]
72. Balabel, A.; Alwetaishi, M.; Abdelhafiz, A.; Issa, U.; Sharaky, I.; Shamseldin, A.; Al-Surf, M.; Al-Harthi, M. Potential of Solatube technology as passive daylight systems for sustainable buildings in Saudi Arabia. *Alex. Eng. J.* **2022**, *61*, 339–353. [CrossRef]
73. Nuvvula, R.S.; Devaraj, E.; Madurai Elavarasan, R.; Iman Taheri, S.; Irfan, M.; Teegala, K.S. Multi-objective mutation-enabled adaptive local attractor quantum behaved particle swarm optimisation based optimal sizing of hybrid renewable energy system for smart cities in India. *Sustain. Energy Technol. Assess.* **2022**, *49*, 101689. [CrossRef]
74. Ponce, P.; Pérez, C.; Fayek, A.R.; Molina, A. Solar energy implementation in manufacturing industry using multi-criteria decision-making fuzzy TOPSIS and S4 framework. *Energies* **2022**, *15*, 8838. [CrossRef]
75. Konhäuser, W. Digitalization in Buildings and Smart Cities on the Way to 6G. *Wirel. Pers. Commun.* **2021**, *121*, 1289–1302. [CrossRef]
76. Pérez-Romero, A.; Mateo-Romero, H.F.; Gallardo-Saavedra, S.; Alonso-Gómez, V.; Alonso-García, M.D.C.; Hernández-Callejo, L. Evaluation of artificial intelligence-based models for classifying defective photovoltaic cells. *Appl. Sci.* **2021**, *11*, 4226. [CrossRef]
77. Zhou, H.; Liu, Q.; Yan, K.; Du, Y. Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 9249387. [CrossRef]
78. Saini, G.S.; Dubey, S.K.; Bharti, S.K. Tracard: A tool for smart city resource management based on novel framework algorithm. *Recent Adv. Comput. Sci. Commun.* **2021**, *14*, 134–140. [CrossRef]
79. Antonopoulos, I.; Robu, V.; Couraud, B.; Flynn, D. Data-driven modelling of energy demand response behaviour based on a large-scale residential trial. *Energy AI* **2021**, *4*, 100071. [CrossRef]
80. Calamaro, N.; Beck, Y.; Ben Melech, R.; Shmilovitz, D. An Energy-Fraud Detection-System Capable of Distinguishing Frauds from Other Energy Flow Anomalies in an Urban Environment. *Sustainability* **2021**, *13*, 10696. [CrossRef]
81. Manman, L.; Goswami, P.; Mukherjee, P.; Mukherjee, A.; Yang, L.; Ghosh, U.; Menon, V.G.; Nkenyereye, L. Distributed Artificial Intelligence Empowered Sustainable Cognitive Radio Sensor Networks: A Smart City on-demand Perspective. *Sustain. Cities Soc.* **2021**, *75*, 103265. [CrossRef]
82. Li, J.; Dai, J.; Issakhov, A.; Almojil, S.F.; Souri, A. Towards decision support systems for energy management in the smart industry and Internet of Things. *Comput. Ind. Eng.* **2021**, *161*, 107671. [CrossRef]
83. Cirella, G.T.; Russo, A.; Benassi, F.; Czermański, E.; Goncharuk, A.G.; Oniszczuk-Jastrzabek, A. Energy re-shift for an urbanizing world. *Energies* **2021**, *14*, 5516. [CrossRef]
84. Hu, Y.C.; Lin, Y.H.; Gururaj, H.L. Partitional clustering-hybridized neuro-fuzzy classification evolved through parallel evolutionary computing and applied to energy decomposition for demand-side management in a smart home. *Processes* **2021**, *9*, 1539. [CrossRef]
85. Mahmood, D.; Latif, S.; Anwar, A.; Hussain, S.J.; Jhanjhi, N.; Sama, N.U.; Humayun, M. Utilization of ICT and AI techniques in harnessing residential energy consumption for an energy-aware smart city: A review. *Int. J. Adv. Appl. Sci.* **2021**, *8*, 50–66. [CrossRef]
86. Wang, X.; Chen, Q.; Wang, J. Fuzzy rough set based sustainable methods for energy efficient smart city development. *J. Intell. Fuzzy Syst.* **2021**, *40*, 8173–8183. [CrossRef]
87. Kanase-Patil, A.B.; Kaldate, A.P.; Lokhande, S.D.; Panchal, H.; Suresh, M.; Priya, V. A review of artificial intelligence-based optimization techniques for the sizing of integrated renewable energy systems in smart cities. *Environ. Technol. Rev.* **2020**, *9*, 111–136. [CrossRef]
88. Jiang, M.; Lu, Y.; Zhu, Z.; Jia, W. Advances in smart sensing and medical electronics by self-powered sensors based on triboelectric nanogenerators. *Micromachines* **2021**, *12*, 698. [CrossRef]
89. Cheng, Y.; Xu, C.; Mashima, D.; Biswas, P.P.; Chipurupalli, G.; Zhou, B.; Wu, Y. PowerNet: A smart energy forecasting architecture based on neural networks. *IET Smart Cities* **2020**, *2*, 199–207. [CrossRef]
90. Loose, N.; Thommessen, C.; Mehlich, J.; Derksen, C.; Eicker, S. Unified energy agents for combined district heating and electrical network simulation. *Sustainability* **2020**, *12*, 9301. [CrossRef]
91. Fattahi, J.; Wright, D.; Schriemer, H. An energy internet DERMS platform using a multi-level Stackelberg game. *Sustain. Cities Soc.* **2020**, *60*, 102262. [CrossRef]
92. Sharma, S. Analysis of intelligent versus smart infrastructure. *Int. J. Adv. Res. Eng. Technol.* **2020**, *11*, 122–132. [CrossRef]
93. Marinakis, V.; Doukas, H.; Koasidis, K.; Albuflasa, H. From intelligent energy management to value economy through a digital energy currency: Bahrain city case study. *Sensors* **2020**, *20*, 1456. [CrossRef] [PubMed]
94. Shah, A.S.; Nasir, H.; Fayaz, M.; Lajis, A.; Ullah, I.; Shah, A. Dynamic user preference parameters selection and energy consumption optimization for smart homes using deep extreme learning machine and bat algorithm. *IEEE Access* **2020**, *8*, 204744–204762. [CrossRef]
95. Guo, Y.; Zhao, Z.; Zhao, R.; Lai, S.; Dan, Z.; Xia, J.; Fan, L. Intelligent Offloading Strategy Design for Relaying Mobile Edge Computing Networks. *IEEE Access* **2020**, *8*, 35127–35135. [CrossRef]
96. Zhuang, H.; Zhang, J.; Sivaparthipan, C.; Muthu, B.A. Sustainable smart city building construction methods. *Sustainability* **2020**, *12*, 4947. [CrossRef]

97. Algieri, A.; Morrone, P.; Bova, S. Techno-economic analysis of biofuel, solar and wind multi-source small-scale CHP systems. *Energies* **2020**, *13*, 3002. [CrossRef]
98. Kumar, D. Urban energy system management for enhanced energy potential for upcoming smart cities. *Energy Explor. Exploit.* **2020**, *38*, 1968–1982. [CrossRef]
99. Aghajani, D.; Abbaspour, M.; Radfar, R.; Mohammadi, A. Using Web-GIS technology as a smart tool for resiliency management to monitor wind farms performances (Ganjeh site, Iran). *Int. J. Environ. Sci. Technol.* **2019**, *16*, 5011–5022. [CrossRef]
100. Oun, A.; Benabdallah, I.; Cherif, A. Improved industrial modeling and harmonic mitigation of a grid connected steel plant in Libya. *Int. J. Adv. Comput. Sci. Appl.* **2019**, *10*, 101–109. [CrossRef]
101. Salehi, H.; Das, S.; Biswas, S.; Burgueño, R. Data mining methodology employing artificial intelligence and a probabilistic approach for energy-efficient structural health monitoring with noisy and delayed signals. *Expert Syst. Appl.* **2019**, *135*, 259–272. [CrossRef]
102. Dong, Y.; Guo, S.; Liu, J.; Yang, Y. Energy-Efficient Fair Cooperation Fog Computing in Mobile Edge Networks for Smart City. *IEEE Internet Things J.* **2019**, *6*, 7543–7554. [CrossRef]
103. Krayem, A.; Al Bitar, A.; Ahmad, A.; Faour, G.; Gastellu-Etchegorry, J.P.; Lakkis, I.; Gerard, J.; Zaraket, H.; Yeretzian, A.; Najem, S. Urban energy modeling and calibration of a coastal Mediterranean city: The case of Beirut. *Energy Build.* **2019**, *199*, 223–234. [CrossRef]
104. Marin-Perez, R.; Michailidis, I.T.; Garcia-Carrillo, D.; Korkas, C.D.; Kosmatopoulos, E.B.; Skarmeta, A. PLUG-N-HARVEST Architecture for secure and intelligent management of near-zero energy buildings. *Sensors* **2019**, *19*, 843. [CrossRef] [PubMed]
105. Aymen, F.; Mahmoudi, C. A novel energy optimization approach for electrical vehicles in a smart city. *Energies* **2019**, *12*, 929. [CrossRef]
106. Khoury, D.; Keyrouz, F. A predictive convolutional neural network model for source-load forecasting in smart grids. *WSEAS Trans. Power Syst.* **2019**, *14*, 181–189.
107. Alhussein, M.; Haider, S.I.; Aurangzeb, K. Microgrid-level energy management approach based on short-term forecasting ofwind speed and solar irradiance. *Energies* **2019**, *12*, 1487. [CrossRef]
108. Risso, C. Benefits of demands control in a smart-grid to compensate the volatility of non-conventional energies. *Rev. Fac. Ing.* **2019**, 19–31. [CrossRef]
109. Njuguna Matheri, A.; Mbohwa, C.; Ntuli, F.; Belaid, M.; Seodigeng, T.; Catherine Ngila, J.; Kinuthia Njenga, C. Waste to energy bio-digester selection and design model for the organic fraction of municipal solid waste. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1113–1121. [CrossRef]
110. Chui, K.T.; Lytras, M.D.; Visvizi, A. Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies* **2018**, *11*, 2869. [CrossRef]
111. Ashfaq, A.; Ianakiev, A. Cost-minimised design of a highly renewable heating network for fossil-free future. *Energy* **2018**, *152*, 613–626. [CrossRef]
112. Laiola, E.; Giungato, P. Wind characterization in Taranto city as a basis for innovative sustainable urban development. *J. Clean. Prod.* **2018**, *172*, 3535–3545. [CrossRef]
113. Rekik, M.; Chtourou, Z.; Mitton, N.; Atieh, A. Geographic routing protocol for the deployment of virtual power plant within the smart grid. *Sustain. Cities Soc.* **2016**, *25*, 39–48. [CrossRef]
114. De Paz, J.F.; Bajo, J.; Rodríguez, S.; Villarrubia, G.; Corchado, J.M. Intelligent system for lighting control in smart cities. *Inf. Sci.* **2016**, *372*, 241–255. [CrossRef]
115. Peña, M.; Biscarri, F.; Guerrero, J.I.; Monedero, I.; León, C. Rule-based system to detect energy efficiency anomalies in smart buildings, a data mining approach. *Expert Syst. Appl.* **2016**, *56*, 242–255. [CrossRef]
116. Huang, J.; Deng, Y.; Yang, Q.; Sun, J. An Energy-Efficient Train Control Framework for Smart Railway Transportation. *IEEE Trans. Comput.* **2016**, *65*, 1407–1417. [CrossRef]
117. Sędziwy, A.; Kotulski, L. Towards highly energy-efficient roadway lighting. *Energies* **2016**, *9*, 263. [CrossRef]
118. Lützenberger, M.; Masuch, N.; Küster, T.; Freund, D.; Voß, M.; Hrabia, C.E.; Pozo, D.; Fähndrich, J.; Trollmann, F.; Keiser, J.; et al. A common approach to intelligent energy and mobility services in a smart city environment. *J. Ambient Intell. Humaniz. Comput.* **2015**, *6*, 337–350. [CrossRef]
119. Fernández, C.; Manyà, F.; Mateu, C.; Sole-Mauri, F. Modeling energy consumption in automated vacuum waste collection systems. *Environ. Model. Softw.* **2014**, *56*, 63–73. [CrossRef]
120. Park, C.J.; Lee, J.; Kim, S.B.; Hyun, J.S.; Park, G.L. Spatio-temporal correlation analysis of wind speed and sunlight for predicting power generation in Jeju. *Int. J. Multimed. Ubiquitous Eng.* **2013**, *8*, 273–282.
121. Riaz, M.; Farid, H.M.A.; Jana, C.; Pal, M.; Sarkar, B. Efficient city supply chain management through spherical fuzzy dynamic multistage decision analysis. *Eng. Appl. Artif. Intell.* **2023**, *126*, 106712. [CrossRef]
122. Guchhait, R.; Sarkar, B. Increasing Growth of Renewable Energy: A State of Art. *Energies* **2023**, *16*, 2665. [CrossRef]