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Review

Advanced Deep Learning Algorithms for Energy Optimization of Smart Cities

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Abstract: Advanced deep learning algorithms play a key role in optimizing energy usage in smart cities, leveraging massive datasets to increase efficiency and sustainability. These algorithms analyze real-time data from sensors and IoT devices to predict energy demand, enabling dynamic load balancing and reducing waste. Reinforcement learning models optimize power distribution by learning from historical patterns and adapting to changes in energy usage in real time. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) facilitate detailed analysis of spatial and temporal data to better predict energy usage. Generative adversarial networks (GANs) are used to simulate energy usage scenarios, supporting strategic planning and anomaly detection. Federated learning ensures privacy-preserving data sharing in distributed energy systems, promoting collaboration without compromising security. These technologies are driving the transformation towards sustainable and energy-efficient urban environments, meeting the growing demands of modern smart cities. However, there is a view that if the pace of development is maintained with large amounts of data, the computational/energy costs may exceed the benefits. The article aims to conduct a comparative analysis and assess the development potential of this group of technologies, taking into account energy efficiency.

Keywords: artificial intelligence; deep learning; smart city; smart buildings; Internet of Things (IoT); energy management; energetic optimization

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1. Introduction

A smart city (and increasingly also an intelligent territory) is a modern, sustainable, and efficiently functioning metropolitan center using advanced technologies and innovative solutions to improve the quality of life of its residents. By integrating resource management systems such as energy, water, transport, communication, and waste management, smart cities strive to achieve harmony between economic development, ecology, and social needs. One of the most important and at the same time most difficult challenges faced by such areas is energy management [1,2]. This results from the dynamically growing demand for energy, the complex nature of energy networks and the need to integrate renewable energy sources. Effective energy management in smart cities requires the use of modern technologies such as the Internet of Things (IoT), artificial intelligence (AI), or advanced data analysis, which enable monitoring and optimization of energy consumption in real time. A key role in energy management is played by smart energy networks (smart grids), which enable two-way communication between energy producers and consumers. Thanks to this, residents can not only consume energy, but also introduce surpluses, e.g., from photovoltaic (PV) installations, to the network. This approach supports the decentralization

of energy systems and enables greater use of renewable energy, which is crucial for reducing greenhouse gas emissions and protecting the environment. At the same time, smart cities focus on educating their residents, promoting a conscious approach to energy consumption, and encouraging the use of energy-saving technologies. Implementing such actions in a sustainable way requires cooperation between local authorities, the private sector, and the community, which makes energy management one of the most complex, but also priority areas in the development of smart cities [1].

The integration of AI in energy optimization for smart cities began with basic rule-based systems that relied on predefined instructions to manage energy distribution and reduce losses. As computing capabilities advanced, machine learning (ML) emerged, enabling systems to analyze historical energy usage data and identify patterns, enabling dynamic and data-driven energy management strategies. Early applications of ML focused on regression models and clustering techniques, optimizing energy demand forecasts and classifying consumption behavior to enable better resource allocation. The evolution of neural networks introduced deep learning (DL), which used multi-layer architectures to process large datasets, increasing the accuracy of energy load forecasting and anomaly detection. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), improved real-time monitoring and predictive maintenance of energy systems, reducing downtime and inefficiencies. Generative AI models, including variational autoencoders (VAEs) and generative adversarial networks (GANs), have further advanced the field by simulating energy scenarios and optimizing grid resilience under hypothetical conditions. The introduction of transformer architectures has revolutionized AI in smart cities, offering improved capabilities for processing sequential energy data, improving the accuracy of long-term forecasting, and enabling more adaptive energy optimization. Transformers like OpenAI's GPT have facilitated smarter energy management strategies with natural language processing (NLP)-enabled systems, enabling seamless communication between energy operators and automated decision-making systems. Today, generative AI applications in energy optimization are exploring advanced scenarios such as microgrid optimization, dynamic integration of renewable energy sources, and creating digital twins for comprehensive simulations of energy ecosystems [1]. Looking ahead, AI algorithms in energy optimization are poised to integrate quantum computing and advanced reinforcement learning, unlocking unprecedented performance and ushering in a new era of energy-smart cities as shown in Figure 1.

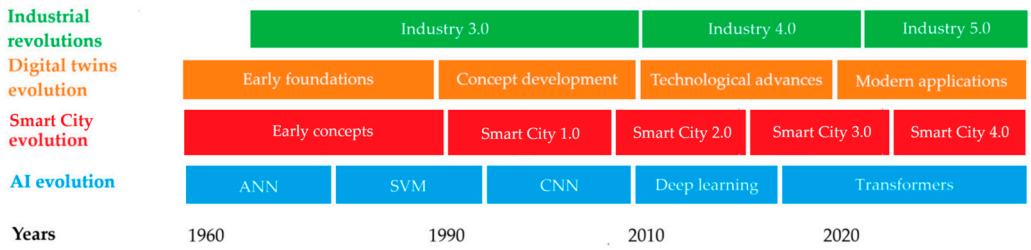


Figure 1. Genesis of DL support for energy optimization of smart cities (own version).

Current advanced DL algorithms play a key role in optimizing energy usage in smart cities, leveraging massive datasets to increase efficiency and sustainability. These algorithms analyze real-time data from sensors and IoT devices to predict energy demand, enabling dynamic load balancing and reducing waste as shown in Figure 2.

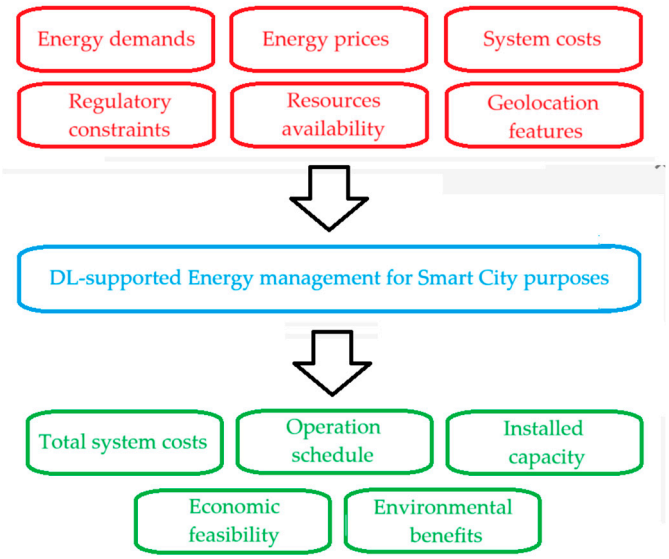


Figure 2. Process of possible DL support for energy optimization of smart cities (own version).

The aim of this article is to assess to what extent DL technologies are developed and used in energy optimization systems for smart cities. The indirect effect will be to indicate functional areas of smart cities and smart territories where DL can be used but currently is notas shown in Table 1.

Table 1. Observed gaps in DL support for energy optimization of smart cities.

Gap	Detailed Description
Data scarcity and quality	Many cities lack sufficient high-quality, labeled data to train robust DL models, leading to suboptimal performance in energy optimization tasks.
Scalability issues	Deploying DL models at the scale required for large smart cities can be computationally expensive, especially for real-time energy optimization involving large and complex datasets.
Integration challenges:	DL models often struggle to integrate seamlessly with existing energy management systems and IoT devices, which can limit their practical utility.
Limited generalization	DL models often struggle to generalize across energy systems and urban environments because they are typically trained on specific datasets that may not represent different scenarios in other cities.
Dynamic system adaptability	Many DL models are not designed to adapt to rapidly changing energy demand and supply dynamics in real time, reducing their effectiveness in volatile energy markets.
Black-box nature	The opaque decision-making process in DL models creates challenges in understanding, debugging, and trusting their recommendations, especially in critical energy optimization scenarios.
Limited focus on renewable energy integration	While DL holds promise, there is a lack of specialized models that fully optimize the integration of renewable energy sources into city grids, addressing intermittency and storage issues.
Cybersecurity risks	Relying on DL systems for energy optimization can expose cities to cybersecurity threats, as vulnerabilities in AI algorithms can be exploited to disrupt critical energy systems.

Table 1. *Cont.*

Gap	Detailed Description
Policy and regulatory compliance	DL solutions are often not compliant with energy policies and city regulations, making their implementation and widespread adoption challenging within smart city regulatory frameworks.

A more detailed statement of the purpose through the research questions (RQs) that the review addresses is as follows: RQ1: evolution of research topics/problems over time; RQ2: geographical distribution of studies/publications, authors, scientific institutions and publications with the highest impact; and RQ3: topics that may shape future research agendas.

2. Materials and Methods

2.1. Dataset

The bibliometric analysis we conducted aimed to investigate the research landscape and the state of knowledge and practice in the area of planning and implementing DL for energy optimization in smart cities and smart territories networks. For this purpose, we used bibliometric methods to analyze recently published scientific publications with a global reach. Our approach includes formulating research questions to identify key areas, which include the current state, evolution of research topics, origin of publications (institutions, country, financing mode), and most influential authors and articles. When possible, we also tried to identify the sustainability goals related to the evaluated publications. This approach allows for obtaining a comprehensive understanding of current research and industry trends in the field of supporting DL-based smart cities and smart territories strategies, research and economic practice, which is essential to understand and plan further developments in this area. By interpreting bibliometric data, this study has the potential to enrich current discussions and establish a solid foundation for future research.

2.2. Methods

In this study, we searched the bibliographic databases Web of Science (WoS), Scopus, PubMed, dblp, EBSCO—Energy & Power Source (EBSCO EPS) and EBSCO—Engineering Source (EBSCO ES) selected for their wide range of studies and rich global data that support deep bibliometric analysis on the use of DL in the energy economy of smart cities as shown in Table 2. Filters were applied to focus on relevant literature, narrowing the scope to articles in English. After filtering, a manual review of each article was conducted to ensure that it met the inclusion criteria, which helped to determine the final sample size. Then, the main features of the dataset were analyzed, including known authors, research groups/institutions, countries, thematic groups and emerging trends. This allowed mapping key terminology and its evolution, as well as the main research achievements in the area. Where possible, temporal trends were tracked to monitor changes in research coverage over time, and publications were grouped into thematic clusters, revealing relationships between different research areas.This process highlighted important topics and subfields within the research area.

The study was based on selected elements of the PRISMA 2020 guidelines for bibliographic reviews [3], focusing on aspects such as rationale (item 3), objectives (item 4), eligibility criteria (item 5), information sources (item 6), search strategy (item 7), selection process (item 8), data collection process (item 9), synthesis methods (item 13a), synthesis results (item 20b), and discussion (item 23a). For the bibliometric analysis, tools embedded in the Web of Science (WoS), Scopus, and dblp databases were used, as well as the Biblioshiny

tool from the Bibliometrix v.4.1.3 package. This selected review methodology supports bibliometric and scientometric studies, often enabling refined categorization by concepts, research areas, authors, documents and sources. The results are presented in a table that allows for flexible analysis and visualization options. Given the interdisciplinary scope and complexity of the topic, we have collected the most important results of the review in a summary table (Supplementary Materials).

Table 2. Bibliometric analysis procedure (own approach).

Stage Name	Tasks
Defining research objectives	Defining goals of the bibliometric analysis
Selecting databases and data collections	Choosing appropriate dataset(s) and developing research queries according to the study goals
Data preprocessing	Cleaning the collected data to remove duplicates and irrelevant records
Bibliometric software selection	Choosing suitable bibliometric software tool for analysis
Data analysis	Description, author, journal, area, topics, institution, country, etc.
Visualization(where possible)	Visualizing the analysis results to present insights
Interpretationand discussion	Interpreting findings in the context of the research goals

2.3. Data Sources

To refine the search, advanced filtered queries were used, limiting the results to articles in English. Searches were performed as follows: in WoS using the "Subject" field (consisting of title, abstract, keywords plus and other keywords); in Scopus using article title, abstract and keywords; and in PubMed, dblp and EBSCO using manual sets of keywords. The databases were searched for articles using keywords such as "deep learning", "smart city", and "energy optimization" or "energy optimisation" as shown in Table 3.

Table 3. Detail search query over databases.

Parameter	Description
Inclusion criteria	Books (and chapters in books), articles (original, reviews, communication, editorials), and conference proceedings, in English
Exclusion criteria	Books older than 10 years, letters, conference abstracts without full text, other languages than English
Keywords used	deep learning, energy optimization/optimisation, smart city
Used field codes (WoS)	"Subject" field (consisting of title, abstract, keyword plus and other keywords)
Used field codes (Sopus)	article title, abstract and keywords
Used field codes (PubMed)	manually
Used field codes (dblp, EBSCO)	manually
Boolean operators used	Yes, e.g., "smart city" AND ("optimization" OR "optimisation") AND "deep learning"
Applied filters	Results refined by publication year, document type (e.g., articles, reviews), and subject area (e.g., industry, engineering).
Iteration and validation options	Query run iteratively, refinement based on the results, and validation by ensuring relevant publications appear among the top hits
Leverage truncation and wildcards used	Used symbols like * for word variations (e.g., "smart cit*" for "smart city" or "smart cities") and ? for alternative spellings (e.g., "optimi?ation")

The selected set of publications was then further refined (as shown in Figure 3) by manually re-screening the articles, removing irrelevant publications and duplicates. This allowed for determining the final sample size. Of the 6 searched databases, out of the 21 publications from databases initial search, only 12 publications passed the entire selection process. The number of citations in the WoS database was in the range of 7–34 (median: 14), all books except one had an Impact Factor score in the range of 2.5–8.2 (median: 3.2).

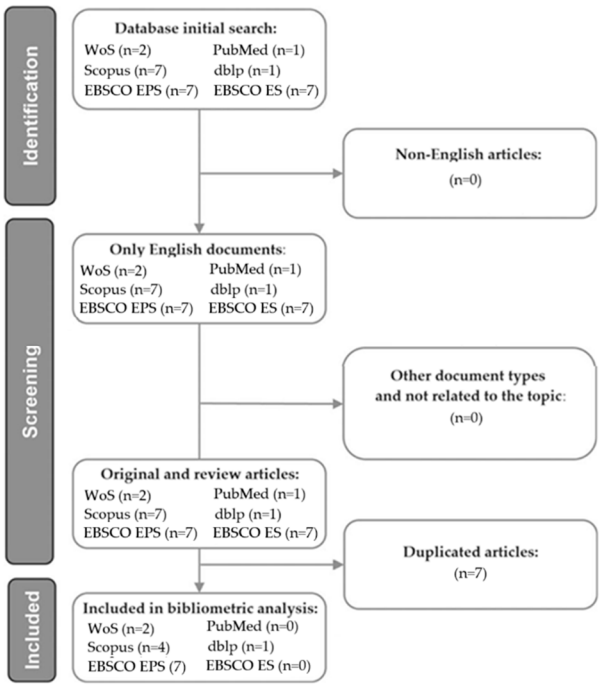


Figure 3. PRISMA flow diagram of the review process using selected PRISMA 2020 guidelines.

3. Results

The summary of the bibliographic analysis results is presented in Table 4. The review included only seven articles published in the last five years (no older ones were included).

Table 4. Summary of results of bibliographic analysis (WoS, Scopus, PubMEd, dblp, EBSCO EPS, EBSCO ES).

Parameter/Feature	Value
Leading types of publication	Article (42.9%), conference review (28.6%), book (14.3%), review (14.3%)
Leading areas of science	Computer science (53.8%), Business, management and accounting (15.4%), Engineering (15.4%), Materials Science (7.7%), Mathematics (7.7%)
Leading topics	Security systems, Sustainability science, Specific emitter identification, Thermal control
Leading countries	India
Leading scientists	None
Leading affiliations	None
Leading funders (where information available)	None
Sustainable development goals	Affordable and clean energy, Sustainable cities and communities, Climate action

Number of publications decreases with year, as shown in Figure 4a. The dominant form of publication so far has been the article, as shown in Figure 4b, and more than half of the publications fell within the discipline of computer science, as shown in Figure 4c.

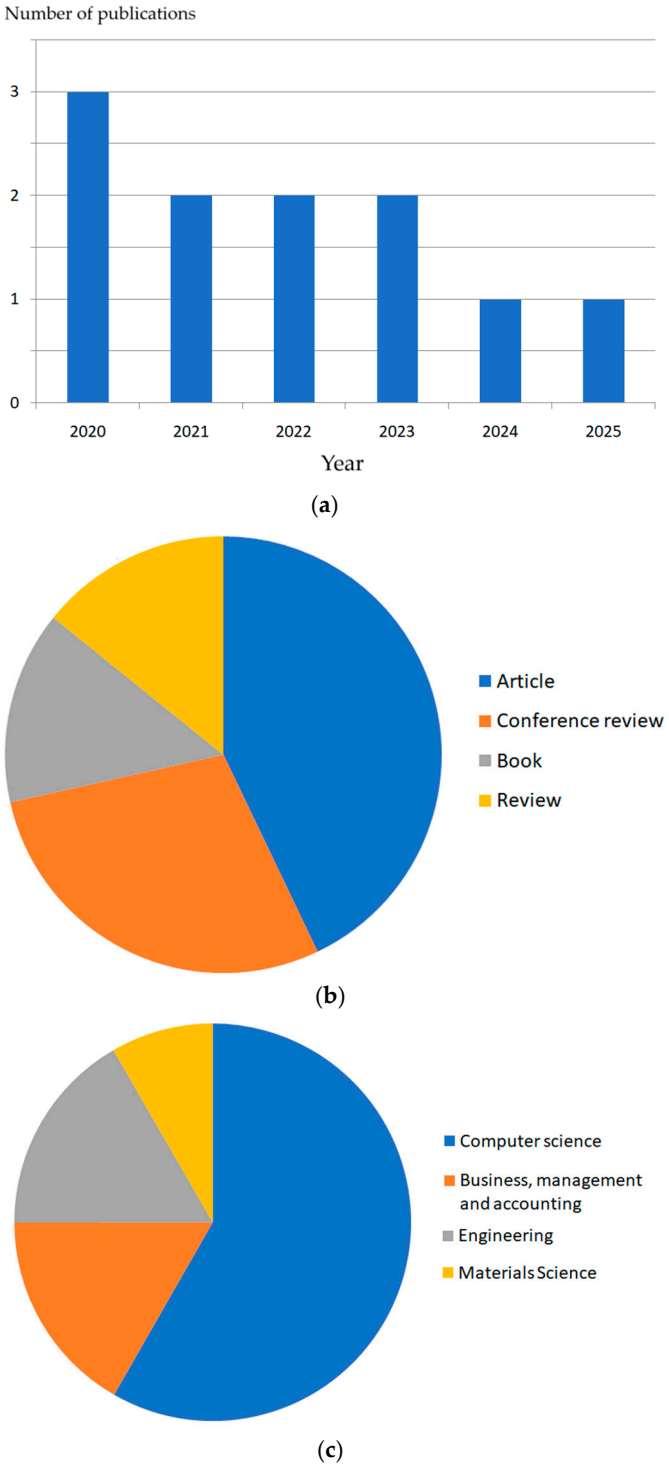


Figure 4. Publications (**a**) by year, (**b**) by type, (**c**) by leading area of science.

3.1. Transformative Role of Deep Learning in Algorithms for Energy Optimization of Smart Cities

DL is revolutionizing energy optimization in smart cities, using its ability to process and analyze vast amounts of complex data. It enables accurate forecasting of energy demand and renewable energy generation, ensuring a balance between supply and consumption. By modelling non-linear relationships, DL enhances the performance of smart

grids, enabling real-time load balancing and minimizing energy losses. DL facilitates the integration of renewable energy sources, such as solar and wind power, predicting their intermittent production with high precision. Adaptive energy management systems, based on deep learning, dynamically optimize energy distribution based on real-time data and evolving patterns. DL also powers smart systems in smart buildings, optimizing heating, ventilation and air conditioning (HVAC) and lighting to reduce energy consumption without compromising comfort.

DL's ability to detect anomalies in energy systems helps prevent failures and inefficiencies, increasing the reliability of the energy infrastructure. Electric vehicle (EV) ecosystems benefit from DL, optimizing vehicle-to-grid (V2G) interactions and synchronizing EV charging with grid requirements. The technology supports personalized energy consumption recommendations, encouraging sustainable habits for residents and businesses. Reinforcement learning (RL) optimizes distributed energy resources, supporting decentralized, resilient energy systems.

Despite its potential, DL brings challenges and risks that need to be neutralized or circumvented. The computational resources required to train DL models contribute to energy consumption, potentially offsetting sustainability benefits; hence, the need for cheaper, less energy-intensive DL solutions available to less demanding customers. Data privacy concerns arise, as energy optimization systems rely on extensive data collection from users and infrastructure. The complexity and opacity of DL models can hinder transparency, making it difficult to understand and trust their decisions. Over-reliance on these systems can lead to vulnerabilities, such as cyber attacks targeting energy optimization algorithms.

DL also raises equity concerns, as its implementation may favor affluent areas over under-served communities due to differences in staffing, the cost of acquiring and maintaining infrastructure and datasets, and the implementation of long-term security and organizational policies. To realise its potential while addressing threats, it is crucial to implement robust security measures, promote transparency and ensure equitable access to advanced energy optimization technologies as shown in Figure 5.

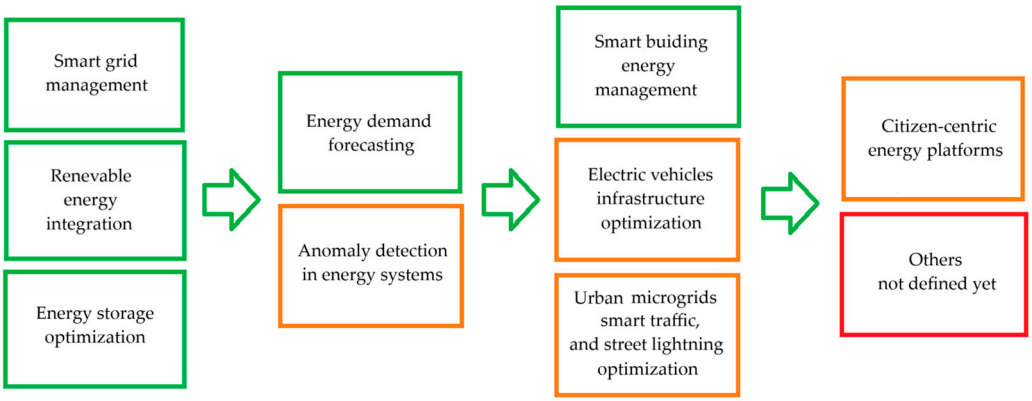


Figure 5. Applications of DL in energy optimization of smart cities. Colors: green: well defined, orange: partly defined, red: not defined yet.

DL is becoming an increasingly integral part of energy optimization in smart cities, enabling smarter, more efficient and sustainable solutions. DL models optimize energy distribution in smart grids by predicting energy demand, identifying faults and dynamically adjusting supply to reduce energy losses. This enables more efficient energy distribution in city networks (e.g., street lighting, bus stops, etc.) [2]. DL algorithms analyze historical consumption patterns, weather data and socio-economic factors to predict energy demand at different times. This helps energy suppliers plan resources and avoid overproduction, taking into account, for example, seasonal and weather changes, time of day, traffic density,

etc., and, in the short term, accidents and traffic jams [4]. Smart buildings use DL to monitor and optimize energy consumption in real time, adjusting HVAC, lighting and other systems based on occupancy, weather and usage patterns [5]. DL helps integrate renewable energy sources such as solar and wind by forecasting generation capacity and managing storage systems. This ensures reliable supply while reducing dependence on non-renewable sources [6]. DL models optimize the placement of EV charging stations, predict charging demand, and manage energy loads at charging stations.This minimizes grid load and increases adoption [7]. DL improves the efficiency of energy storage systems such as batteries by predicting usage patterns and determining optimal charging and discharging schedules [8]. DL-based systems optimize energy use in traffic management and street lighting. For example, adaptive lighting systems dim or brighten lights based on pedestrian and vehicle activity [9]. DL models detect anomalies such as energy theft, equipment failures, or inefficient utilization in real time, enabling rapid corrective actions [10]. Microgrids in smart cities can operate partially independently of the main grid. DL optimizes their operation by balancing loads, integrating renewable energy sources and managing energy exchanges with the main grid [11]. DL-based platforms enable citizens to optimize their personal energy consumption with personalized recommendations. They can track and manage their consumption, leading to increased awareness and energy savings [12].

3.2. Identified Trends and Solutions

Earlier trends in the application of DL to optimize energy use in smart cities have mainly focused on predictive modelling and data analysis. Early efforts used DL to predict energy demand and supply, enabling better planning and reducing waste. Researchers have also explored the integration of renewable energy, using models to predict power from solar and wind sources. Anomaly detection in power grids was another early application, helping to identify faults and inefficiencies. Current trends indicate a shift towards more sophisticated, decentralized, real-time applications. Real-time optimization of energy systems now uses DL with reinforcement to dynamically adapt to changing conditions. Smart buildings are increasingly using deep learning for personalized energy management, optimizing HVAC and lighting systems based on occupancy and outdoor conditions. Integration with electric vehicle (EV) ecosystems is becoming more common, focusing on vehicle-to-network (V2G) energy balancing. Advanced neural networks are now facilitating distributed energy systems, improving resilience and sustainability by optimizing localized energy resources. In addition, there is growing interest in using deep learning to engage citizens, providing tailored energy-saving recommendations and insights to promote sustainable habits.

To optimize the benefits, it is important to predict the maximum electrical output of the base-cycle plant, the hourly electrical output of the combined-cycle plant at full load. In order to achieve higher accuracy, deep extreme machine learning (DELM) was another candidate to be investigated for data sequence analysis. It achieved a high level of reliability with minimal error: the highest accuracy rate was 98.6% with a split of 70% training (33488 samples), 30% test and validation (14352 examples) [13]. This requires continuous improvement and verification of the reliability of device indications. Smart grids include energy devices used for energy optimization based on IoT and its services. Stable operation of such smart grids requires maintaining IoT cybersecurity using cryptographic security methods and non-cryptographic methods (e.g., radio frequency fingerprinting—RFF) [14]. RFF, combined with DL-based cybersecurity [15], already today allows for classification and detection of rogue devices based on reported hardware damage in IoT device radios. In the case of smart energy-efficient buildings, DL plays an important role in predicting heat loads for the overall energy efficiency analysis. DL algorithms are an important complement to stochastic algorithms, which have proven their worth here. Hence, mixed

solutions are considered, such as hybrid methods for predicting cooling loads in residential buildings. Models that combine artificial neural networks and stochastic fractal search, the Grasshopper optimization algorithm and the Firefly algorithm can cope with the nonlinear impact of eight independent factors on the model with a correlation of over 90% with varying degrees of success [16]. IoT and M technologies are already widely used in smart energy-efficient buildings, in particular for analyzing and predicting the impact of temperature, humidity, lighting, occupancy and occupant behavior to optimize building systems, as shown, e.g., in the review by Islam et al. [17]. However, DL applications are only just emerging in smart energy-efficient building applications, further pushing the boundaries of analysis, inference and prediction. It is necessary to develop new technologies for intelligent energy management in buildings based on DL in order to show the real effects of energy savings and promote the above-mentioned solutions. It should be noted that so far no solutions to such complex problems have been shown in real time also using traditional methods [18]. The current challenges for DL in this area of application are as follows:

- A lack of accurate models of thermal dynamics of a building efficient enough to control the building;
- A number of uncertain (and sometimes: difficult to predict or estimate) parameters of the system;
- Numerous spatially and temporally coupled operational constraints;
- A large number of alternative scenarios and extensive solution spaces;
- Energy management methods in buildings have strict assumptions and low flexibility with a large variety of building environments [18].

The applications of combining IoT and deep reinforcement learning (DRL) are particularly promising [18]. An additional problem in the face of the energy crisis is the vertical areas of the smart city with IoT devices with limited energy resources and little possibilities for energy optimization. In case of inability to increase energy efficiency, an intelligent framework based on software-defined wireless networks and edge computing must be applied. From a computational point of view, it is based on the synergistic integration of dual deep reinforcement learning and matching game theory for multi-connectivity and guaranteed service provisioning under radio access constraints. This gives an improvement of 45% in overall energy efficiency [19]. It is necessary to quickly bridge the gap between the use of traditional energy consumption analysis methods and the use of modern consumption methods using AI, especially DL, which can be cheaper and more efficient in the long run and at a large scale. They can also correct significant limitations in energy consumption and its optimization regardless of industries and application areas [20]. Energy optimization must take into account a number of constraints. Indicators of occupant comfort (thermal, visual and air quality) can be based on measurements and predictions of parameters (temperature, lighting and CO_2).Until now, these were rather static user parameters declared once at the beginning. Currently, the DL-based approach predicts the above-mentioned parameters for a given user based on the Bat algorithm and fuzzy logic, optimizing energy consumption and ensuring user comfort [21]. This is also possible thanks to fuzzy weather prediction [22]. The parameters predicted in this way have improved the ease of use of intelligent systems, reduced energy consumption and comfort indicator management. The study of the implementation of a demand-side management (DSM) aggregator model in smart cities in the retail industry regarding energy saving awareness and the application of deep learning techniques showed the high effectiveness of the aggregator model, where the mean square prediction error (MSPE) was below 2.05% [23]. Recent advances in DL models pave the way for designing efficient energy management schemes. Here, we propose an artificial jellyfish optimization model with deep learning for

decision support (AJODL-DSSEM) that performs data preprocessing at the initial stage to normalize the data and a convolutional neural network–bidirectional short-term memory (CNN-ABLSTM) model for energy prediction with an RMSE of 0.384 [24].

The problem in the case of smart devices is the higher energy consumption compared to regular buildings; hence, the importance of optimizing energy consumption in smart buildings or smart homes [21]. Each of these systems has its own unique features, can be combined in many ways, and is designed for different applications and budgets as shown in Table 5.

Table 5. Diverse possible devices and services for DL-based energetic optimization in smart homes (own version).

Function				
Control center				
Controllers	Voice control	Daily fixed features	Handling routines and automation	Smart assistant
Integration with multiple devices and external services				
Climate control	Lighting(including blinds)	Cameras and sensors	Privacy	Security
Smart Things Hub				
Intelligent kitchen utilities	Smartwatch, smartband, in-sole	Smartphone, tablet	Brain–computer interfaces	Virtual reality, Augmented reality
Networks				
Z-Wave	Zigbee	Wi-Fi	LoRaWAN	Bluetooth
Entertainment				
Smart TV, home cinema	Audio systems	Gaming consoles	Smart exercise devices	Movement/activity control
Others				
eHealth devices	Communication devices	Access to real-world data	eWork	eLearning

DL has made remarkable progress, as CNNs and RNNs have allowed the transition to transformers that learn long-range dependencies efficiently but outperform RNNs rather in machine translation and text analysis [25]. Transfer learning leverages pre-trained knowledge from massive datasets, reducing the need for large labeled datasets towards LLM, as shown in Figure 6 [26].

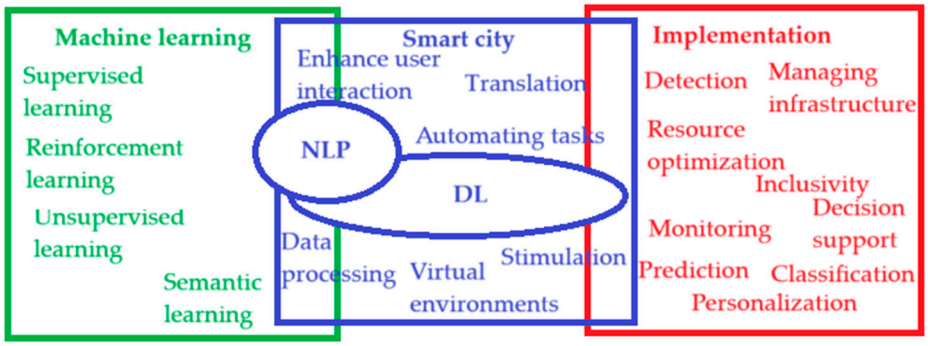


Figure 6. Role of DL in smart city applications (own version).

Table 6 shows how each DL technology leverages specific capabilities to address the challenges of energy optimization in smart cities, with different strengths and limitations depending on the data and objectives.

Table 6. Comparison of various DL technologies used for energy optimization in a smart home (own version).

Technology	Primary Application	Strengths	Limitations
Convolutional Neural Networks (CNNs)	Analysis of spatial data such as energy consumption patterns across geographic regions	It processes spatial data well, such as maps and satellite images. It effectively identifies energy consumption trends in specific areas	Requires large amounts of labeled data for training. Inefficient in processing temporal data
Recurrent Neural Networks (RNNs)	Analyzing temporal data to predict fluctuations in energy demand and supply over time	Efficiently handles sequential data. Effectively predicts seasonal or time-dependent (day of week, time of day, etc.) energy demands	Cannot handle long-term dependencies. Requires high computational power. Susceptible to vanishing gradients
Generative Adversarial Networks (GANs)	Simulation of energy consumption scenarios and detection of anomalies in smart energy grids	Ability to generate synthetic datasets for scenario planning. High efficiency in detecting anomalies	Training is complex and requires careful balancing of generator and discriminator. It is resource-intensive.

Smart grids and energy systems already monitor, predict energy demand, and adapt to changes in energy demand and supply. This allows for more proactive decision-making planning in energy infrastructure based on real data and more accurate estimation, based on DL, and based not only on historical data but also on predicted values of many parameters [27]. These systems must handle the integration of renewable energy sources, intelligent storage solutions, decentralized microgrids, and groups of intelligent loads. This can account for up to 30% of energy consumption, being crucial for energy stability, reliability, and sustainable development [28]. With such a high share, DL as a more accurate solution effectively increases the efficiency and reliability of renewable energy use, enabling its better forecasting and thus accurate forecasting of energy supply, its balancing, and network management [29]. Additionally, when integrated with digital twins (DTs) of power grid devices, distribution networks, and energy consumers (including consumer behavior) and the interactions between them, ways to optimize energy consumption in residential, office, and service buildings themselves, urban infrastructure (e.g., street and parking lighting, information and parking meters, public transport stops and electric vehicles, e.g., trams, trolleybuses and buses) as far as eHealth services are indicated [30–32]. It is also important to maintain the efficiency of the network, uninterrupted energy supply, and remote maintenance and predictive maintenance of geographically dispersed energy resources of smart cities and smart territories [33]. This is achieved through remote assistance and virtual site inspections based on advanced data analysis and real-time monitoring. This is especially true for the prediction and integration of data from wind and solar power plants in order to accurately forecast energy production in smart microgrids. This provides full situational awareness at any time in the present and accurate models for the future, also within the Energy Internet of Things [34]. This contributes to increasing the trust of decision-makers and citizens in renewable energy sources and the creation of sustainable urban environments or territories [35,36].

4. Discussion

The success of a smart city depends on the ability to combine innovative energy technologies with care for the needs of residents and the environment, making it a place friendly to live both today and in the future [37].

4.1. Limitations of Own Study

DL models often have difficulty generalizing beyond the specific data on which they are trained, making it difficult to adapt to the diverse and dynamic conditions in smart cities [38]. High-quality, labeled data sets for energy optimization are often scarce, leading to models being trained on incomplete or noisy data, which can hinder performance [39]. Training and implementing DL models require significant computational resources, which ironically increases energy consumption and runs counter to sustainability goals. Many DL algorithms are not inherently scalable, and extending them to applications involving millions of nodes across a city can be computationally prohibitive [40]. Smart urban energy systems require real-time decision-making, but DL models often face latency issues due to complex calculations. DL models are unfortunately often black-box systems, making it difficult for stakeholders to understand or trust their decisions in critical energy optimization scenarios [41,42]. Smart cities often have legacy energy infrastructure, and integrating DL solutions with these legacy systems can be technically challenging [43]. The dynamic and unpredictable nature of urban environments, such as varying energy demand and weather conditions, makes it difficult for DL models to maintain accuracy over time [44]. Data privacy regulations and ethical concerns over the use of personal and energy consumption data can limit the development and deployment of DL models [45].

Technological constraints, as shown in Table 7, significantly impact the feasibility of implementing deep learning algorithms for energy optimization in smart cities. These constraints affect the scalability, real-time adaptability, and overall reliability of such solutions, hindering their widespread adoption. Addressing these constraints is essential to provide robust, efficient, and practical energy optimization systems that can operate effectively in the complex and dynamic environments of smart cities [46].

Table 7. Technical limitations of application of deep learning algorithms for energy optimization of smart cities (own version).

Technical Limitation	Description
Dynamic nature of energy systems	Energy demand and supply in smart cities are highly dynamic, and DL models may have difficulty adapting quickly to sudden changes or unforeseen events.
Data scarcity and quality	DL algorithms require large amounts of high-quality data for training, but smart city energy systems often face challenges in collecting sufficient, reliable, and diverse data, especially in developing regions.
Computational complexity	The high computational power required to train DL models can be a limitation, especially when trying to optimize energy systems in real time.
Interpretation issues	DL models often act as black boxes, making their decisions difficult to interpret, which can hinder trust and adoption in critical energy optimization tasks.
Generalization challenges	Models trained in specific urban environments may not generalize to others due to differences in infrastructure, climate, and energy demand patterns.
Integration challenges	Integrating deep learning algorithms with existing legacy energy systems and infrastructure in smart cities can be complex and expensive.
Heavy reliance on IoT sensors and devices	Deep learning requires accurate, real-time data, which relies on extensive deployment of IoT sensors and devices, making the system vulnerable to hardware failures and cybersecurity threats.

Table 7. *Cont.*

Technical Limitation	Description
Energy consumption of models:	Energy-intensive training and operation of DL models can counteract the energy-saving goals of smart city optimization.
Limited real-world testing	Many DL energy optimization solutions are developed and validated in simulations, making their performance in real-world scenarios uncertain.

Practical constraints, as shown in Table 8, significantly impact their implementation in smart cities. These challenges can delay adoption, reduce efficiency, and create barriers for smaller cities or cities with limited resources to implement such technologies. Overcoming these constraints is crucial to enabling equitable, scalable, and sustainable energy optimization solutions that will benefit diverse urban environments [47].

Table 8. Practical limitations of application of deep learning algorithms for energy optimization of smart cities (own version).

Practical Limitation	Description
High implementation costs	Implementing DL for energy optimization requires significant investments in computing infrastructure, data collection systems, and skilled personnel, which can strain city budgets.
Lack of skilled specialists	Many cities lack specialists with experience in DL, energy systems, and their integration, delaying implementation and optimization efforts.
Real-time constraints:	Optimizing energy usage requires timely decision-making, and deep learning models can struggle to process real-time data due to computational latency or delays.
Maintenance and scalability challenges	Keeping models updated and scalable as city infrastructure and energy needs evolve is a practical hurdle, requiring constant tuning and resources.
Dependence on reliable connectivity	Smart city environments are highly dependent on stable internet and communication networks to feed real-time data to deep learning systems, which is not always guaranteed.
Vulnerability to cyberattacks	Reliance on interconnected systems and IoT devices exposes deep learning-based solutions to hacking, making it difficult to optimize energy usage.

Ethical and social implications play a key role in ensuring fair, transparent, and inclusive deployment of deep learning algorithms for energy optimization in smart cities. Addressing issues such as privacy, bias, and equitable access strengthens public trust and ensures that these technologies benefit all citizens without exacerbating existing inequalities. By incorporating ethical considerations into design and implementation, cities can achieve sustainable energy goals while respecting societal values and promoting long-term acceptance [48], as shown in Table 9.

Table 9. Ethical and social implications of application of deep learning algorithms for energy optimization of smart cities (own version).

Practical Limitation	Description
Stakeholder resistance	Convincing city governments, utility providers, and the public to adopt and trust deep learning for energy optimization can be difficult due to perceived risks and lack of awareness.
Environmental impact of training models	The significant energy consumption during training and running of deep learning models can be counter to the goal of optimizing energy consumption, leading to practical sustainability concerns.

Table 9. *Cont.*

Practical Limitation	Description
Privacy concerns	DL algorithms often rely on detailed energy consumption data from households and businesses, raising concerns about the invasion of privacy and misuse of sensitive information.
Algorithm bias	Models trained on biased or incomplete datasets can lead to unfair energy distribution, disproportionately affecting disadvantaged communities or areas with less historical representation.
Transparency and trust	The black-box nature of deep learning algorithms makes it difficult for stakeholders to understand how decisions are made, which undermines trust and potentially leads to public resistance.
Digital gap	Reliance on advanced technologies can exacerbate inequality, as wealthier regions can benefit more from optimization systems while leaving economically disadvantaged areas behind.
Liability issues	When energy optimization decisions cause unintended consequences, such as power outages or unfair billing, it can be unclear who is responsible—the algorithm creators, the system operators, or the city government.

4.2. Directions for Further Studies

Research should focus on developing methods to collect, preprocess, and augment data to optimize energy consumption to address the challenges of scarcity and noise in smart city datasets. Researchers are exploring lightweight and energy-efficient deep learning models, such as pruning and quantization, to reduce the computational load and carbon footprint of these algorithms [49]. Advances in streaming and online learning algorithms continue to enable deep learning models to make accurate and fast decisions in dynamic energy optimization scenarios. Efforts are being made to adapt pre-trained models to new environments and datasets, improving the scalability and generalizability of energy optimization solutions [50]. Research is underway to combine deep learning with IoT devices and Edge Computing platforms to process energy data locally and reduce latency in smart city applications. The development of interpretable deep learning models is a key area of focus to improve transparency, trust, and adoption in energy management systems [51]. Research is underway to create adaptive models that can be continuously updated and retrained to adapt to the ever-changing conditions of urban energy systems. Innovative optimization techniques, such as reinforcement learning and hybrid approaches combining deep learning with optimization algorithms, are being developed to improve energy efficiency. Interdisciplinary research combining insights from fields such as urban planning, energy systems engineering, and artificial intelligence is prioritized to create holistic solutions for smart cities [52]. Methods such as federated learning and differentiated privacy are explored to ensure that energy optimization using deep learning respects user privacy and complies with regulatory requirements [53,54].

Industry and society are ready for the next big leap towards Industry 5.0, and the related socio-economic and technological challenges within the so-called "sustainable development trilemma" taking into account three pillars of sustainable development simultaneously: economic, social, and environmental [55]. We already know that Society 5.0 brings with it a framework in which AI, IoT, and other future digital innovations will be seamlessly integrated into society for sustainable, equitable, and human-centric development and sustainable management of resources, including energy [56,57].This is expected to shift the emphasis from a technology race to human-centric values. This is particularly true for increasing resource efficiency in the energy and water sectors and minimizing their environmental impact through synergy between circular economy practices and sustainable economic development [58–60].

5. Conclusions

Energy forecasting and optimization are key to preventing energy waste, using it in a planned manner, and reducing its cost. The implementation of efficient renewable energy systems for smart cities, smart territories, and other green technologies is complicated, and the combination of IoT and DL is one of the main ways to achieve this goal. Already now, DL allows achieving prediction accuracy above 90%, and in some cases 98%. These values will increase with the number of devices subject to validation and monitoring, so that they are fully predictable, both in terms of power consumption during proper operation, as well as various types of failures and even substitute scenarios. Such advancement will improve operational awareness and increase the trust of decision-makers and ordinary citizens in systems based on DL as reliable and accurate, and sometimes: predicting correct and incorrect behavior of devices and their users.This will increase the comfort of residents of smart cities and smart territories, while reducing the costs of providing it through better sustainability and wider use of cheaper renewable energy sources.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
CNN	Convolutional neural network
DL	Deep learning
DRL	Deep reinforcement learning
EBSCO EPS	EBSCO—Energy & Power Source
EBSCO ES	EBSCO—Engineering Source
EV	Electric vehicle
GAN	Generative adversarial network
HVAC	Heating, ventilation, and air conditioning
IoT	Internet of Things
LLM	Large Linguistic Model
ML	Machine learning
NLP	Natural language processing
PV	Photovoltaic
RFF	Radio frequency fingerprinting
RL	Reinforcement learning
RNN	Recurrent neural networks

RQ	Research question
V2G	Vehicle-to-grid
VAE	Variational autoencoder

References

1. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M. Machine Learning- and Artificial Intelligence- Derived Prediction for Home Smart Energy Systems with PV Installation and Battery Energy Storage. *Energies* **2023**, *16*, 6613. [CrossRef]
2. Bernardes Chagas Barros, E.; Souza, W.O.; Costa, D.G.; Filho, G.P.R.; Figueiredo, G.B.; Peixoto, M.L.M. Energy management in smart grids: An Edge-Cloud Continuum approach with Deep Q-learning. *Future Gener. Comput. Syst.* **2025**, *165*, 107599. [CrossRef]
3. 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. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]
4. Kausar, F.; Al-Hamouz, R.; Hussain, S. Energy Demand Forecasting for Electric Vehicles Using Blockchain-Based Federated Learning. *IEEE Access* **2024**, *12*, 41287–41298. [CrossRef]
5. Watari, D.; Marantos, C.; Taniguchi, I.; Catthoor, F.; Siozios, K.; Soudris, D.; Onoye, T. Online Energy Management Framework for Smart Buildings With Low-Complexity Estimators. *IEEE Embed. Syst. Lett.* **2024**, *16*, 138–141. [CrossRef]
6. Abdelsattar, M.; Ismeil, M.A.; Aly, M.M.; Abu-Elwfa, S.S. Analysis of Renewable Energy Sources and Electrical Vehicles Integration Into Microgrid. *IEEE Access* **2024**, *12*, 66822–66832. [CrossRef]
7. Balogun, E.; Buechler, E.; Bhela, S.; Onori, S.; Rajagopal, R. EV-EcoSim: A Grid-Aware Co-Simulation Platform for the Design and Optimization of Electric Vehicle Charging Infrastructure. *IEEE Trans. Smart Grid* **2024**, *15*, 3114–3125. [CrossRef]
8. Rizqi, Z.U.; Chou, S.Y.; Khairunisa, A. Multi-objective simulation-optimization for integrated automated storage and retrieval systems planning considering energy consumption. *Comput. Ind. Eng.* **2024**, *189*, 109979. [CrossRef]
9. Andrysiak, T.; Saganowski, Ł. Neural Network Analysis of PLC Traffic in Smart City Street Lighting Network. In Proceedings of the 13th International Conference on Computational Intelligence in Security for Information Systems (CISIS), Burgos, Spain, 16–18 September 2020; pp. 436–445.
10. Andronikidis, G.; Eleftheriadis, C.; Batzos, Z.; Kyranou, K.; Maropoulos, N.; Sargsyan, G.; Radoglou-Grammatikis, P.I.; Sarigiannidis, P.G. AI-Driven Anomaly and Intrusion Detection in Energy Systems: Current Trends and Future Direction. In Proceedings of the 2024 IEEE International Conference on Cyber Security and Resilience (CSR), London, UK, 2–4 September 2024; pp. 777–782.
11. Jing, L.; Guo, J.; Feng, T.; Han, L.; Zhou, Z.; Melikuziev, M. Research on Energy Optimization Scheduling Methods for Systems with Multiple Microgrids in Urban Areas. In Proceedings of the 2024 IEEE 4th International Conference on Digital Twins and Parallel Intelligence (DTPI), Wuhan, China, 18–20 October2024; pp. 706–711.
12. Boekelo, M.; Kloppenburg, S. Energy platforms and the future of energy citizenship. *Energy Res. Soc. Sci.* **2023**, *102*, 103165. [CrossRef]
13. Abbas, S.; Khan, M.A.; Falcón-Morales, L.E.; Rehman, A.; Saeed, Y.; Zareei, M.; Zeb, A.; Mohamed, E.M. Modeling, Simulation and Optimization of Power Plant Energy Sustainability for IoT Enabled Smart Cities Empowered With Deep Extreme Learning Machine. *IEEE Access* **2020**, *8*, 39982–39997. [CrossRef]
14. Awan, M.A.; Dalveren, Y.; Catak, F.O.; Kara, A. Deployment and Implementation Aspects of Radio Frequency Fingerprinting in Cybersecurity of Smart Grids. *Electronics* **2023**, *12*, 4914. [CrossRef]
15. Czeczot, G.; Rojek, I.; Mikołajewski, D.; Sangho, B. AI in IIoT Management of Cybersecurity for Industry 4.0 andIndustry 5.0 Purposes. *Electronics* **2023**, *12*, 3800. [CrossRef]
16. Moayedi, H.; Mosavi, A. Suggesting a Stochastic Fractal Search Paradigm in Combination with Artificial Neural Network for Early Prediction of Cooling Load in Residential Buildings. *Energies* **2021**, *14*, 1649. [CrossRef]
17. Islam, M.B.; Guerrieri, A.; Gravina, R.; Frtino, A. A Meta-Survey on Intelligent Energy-Efficient Buildings. *Big DataCogn. Comput.* **2024**, *8*, 83. [CrossRef]
18. Yu, L.; Qin, S.; Zhang, M.; Shen, C.; Jiang, T.; Guan, X. A Review of Deep Reinforcement Learning for Smart Building Energy Management. *IEEE Internet Things J.* **2021**, *8*, 12046–12063. [CrossRef]
19. Priya, B.; Malhotra, J. Intelligent Multi-connectivity Based Energy-Efficient Framework for Smart City. *J. Netw. Syst. Manag.* **2023**, *31*, 48. [CrossRef]
20. John, A.; Mohan, S.K.; Padmanaban, S.; Hamid, Y. *Hybrid Intelligent Approaches for Smart Energy: Practical Applications*; Scrivener Publishing: Austin, TX, USA, 2022; pp. 1–336.
21. 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]

22. Małolepsza, O.; Mikołajewski, D.; Prokopowicz, P. Using Fuzzy Logic to Analyse Weather Conditions. *Electronics* **2025**, *14*, 85. [CrossRef]
23. Carrera, B.; Kim, K. A Regression Framework for Energy Consumption in Smart Cities with Encoder-Decoder Recurrent Neural Networks. *Energies* **2023**, *16*, 7508. [CrossRef]
24. Shah, S.F.A.; Iqbal, M.; Aziz, Z.; Rana, T.A.; Khalid, A.; Cheah, Y.-N.; Arif, M. The Role of Machine Learning and the Internet of Things in Smart Buildings for Energy Efficiency. *Appl. Sci.* **2022**, *12*, 7882. [CrossRef]
25. Cicirelli, F.; Guerrieri, A.; Vinci, A.; Spezzano, G. *IoT Edge Solutions for Cognitive Buildings*; Springer: Berlin/Heidelberg, Germany, 2022.
26. Ngarambe, J.; Adilkhanova, I.; Uwiragiye, B.; Yun, G.Y. A review on the current usage of machine learning tools for day lighting design and control. *Build. Environ.* **2022**, *223*, 109507. [CrossRef]
27. Runge, J.; Zmeureanu, R. Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review. *Energies* **2019**, *12*, 3254. [CrossRef]
28. Olesiński, A.; Piotrowski, Z. An adaptive energy saving algorithm for an rssi-based localization system in mobile radio sensors. *Sensors* **2021**, *21*, 3987. [CrossRef]
29. Ulloa-Vásquez, F.; Heredia-Figueroa, V.; Espinoza-Iriarte, C.; Tobar-Ríos, J.; Aguayo-Reyes, F.; Carrizo, D.; García-Santander, L. Model for Identification of Electrical Appliance and Determination of Patterns Using High-Resolution Wireless Sensor NETWORK for the Efficient Home Energy Consumption Based on Deep Learning. *Energies* **2024**, *17*, 1452. [CrossRef]
30. Rojek, I.; Mikołajewski, D.; Dostatni, E.; Kopowski, J. Specificity of 3D Printing and AI-Based Optimization of Medical Devices Using the Example of a Group of Exoskeletons. *Appl. Sci.* **2023**, *13*, 1060. [CrossRef]
31. Kawala-Sterniuk, A.; Pelc, M.; Martinek, R.; Wójcik, G.M. Editorial: Currents in biomedical signals processing—Methods and applications. *Front. Neurosci.* **2022**, *16*, 989400. [CrossRef] [PubMed]
32. Różanowski, K.; Sondej, T. Architecture Design of the High Integrated System-on-Chip for Biomedical Applications. In Proceedings of the 20th International Conference on Mixed Design of Integrated Circuits and Systems (MIXDES), Gdynia, Poland, 20–22 June 2013; pp. 529–533.
33. Rojek, I.; Dostatni, E.; Mikołajewski, D.; Pawłowski, L.; Wegrzyn-Wolska, K. Modern approach to sustainable production in the context of Industry 4.0. *Bull. Pol. Acad. Sci. Tech. Sci.* **2022**, *70*, e143828. [CrossRef]
34. Mazur, D.; Wachta, H.; Lesko, K. Research of Cohesion Principlein Illuminations of Monumental Objects. 13th Scientific Conference on Selected Issues of Electrical Engineering and Electronics (WZEE). *Anal. Simul. Electr. Comput. Syst.* **2018**, *452*, 395–406.
35. Krajewski, D.; Oleksy, M.; Oliwa, R.; Bulanda, K.; Czech, K.; Mazur, D.; Masłowski, G. Methods for Enhancing the Electrical Properties of Epoxy Matrix Composites. *Energies* **2022**, *15*, 4562. [CrossRef]
36. Zareba, M.; Cogiel, S.; Danek, T.; Weglinska, E. Machine Learning Techniques for Spatio-Temporal Air Pollution Prediction to Drive Sustainable Urban Development in the Era of Energy and Data Transformation. *Energies* **2024**, *17*, 2738. [CrossRef]
37. Necula, S.-C. Assessing the Potential of Artificial Intelligence in Advancing Clean Energy Technologies in Europe: A Systematic Review. *Energies* **2023**, *16*, 7633. [CrossRef]
38. Lifelo, Z.; Ding, J.; Ning, H.; Qurat-Ul-Ain; Dhelim, S. Artificial Intelligence-Enabled Metaverse for Sustainable Smart Cities: Technologies, Applications, Challenges, and Future Directions. *Electronics* **2024**, *13*, 4874. [CrossRef]
39. Almaleh, A. A Novel Deep Learning Approach for Real-Time Critical Assessment in Smart Urban Infrastructure Systems. *Electronics* **2024**, *13*, 3286. [CrossRef]
40. Portase, R.L.; Tolas, R.; Potolea, R. Smart Laundry: A Real-Time System for Public Laundry Allocation in Smart Cities. *Sensors* **2024**, *24*, 2159. [CrossRef] [PubMed]
41. Chen, X.; Liu, G. Federated Deep Reinforcement Learning-Based Task Offloading and Resource Allocation for Smart Cities in a Mobile Edge Network. *Sensors* **2022**, *22*, 4738. [CrossRef] [PubMed]
42. Sultan, S.M.; Waleed, M.; Pyun, J.-Y.; Um, T.-W. Energy Conservation for Internet of Things Tracking Applications Using Deep Reinforcement Learning. *Sensors* **2021**, *21*, 3261. [CrossRef]
43. Yao, C.-B.; Kao, C.-Y. Enhancing Energy Efficiency in Retail within Smart Cities through Demand-Side Management Models. *Appl. Sci.* **2023**, *13*, 13040. [CrossRef]
44. Al-Qarafi, A.; Alsolai, H.; Alzahrani, J.S.; Negm, N.; Alharbi, L.A.; Al Duhayyim, M.; Mohsen, H.; Al-Shabi, M.; Al-Wesabi, F.N. Artificial Jellyfish Optimization with Deep-Learning-Driven Decision Support System for Energy Management in Smart Cities. *Appl. Sci.* **2022**, *12*, 7457. [CrossRef]
45. Tian, K.; Chai, H.; Liu, Y.; Liu, B. Edge Intelligence Empowered Dynamic Offloading and Resource Management of MEC for Smart City Internet of Things. *Electronics* **2022**, *11*, 879. [CrossRef]
46. Wolniak, R.; Stecuła, K. Artificial Intelligence in Smart Cities—Applications, Barriers, and Future Directions: A Review. *Smart Cities* **2024**, *7*, 1346–1389. [CrossRef]

47. 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]
48. Wang, B. Ethical Reflections on the Application of Artificial Intelligence in the Construction of Smart Cities. *J. Eng.* **2024**, *1*, 8207822. [CrossRef]
49. An, S.; Shi, H.; Hu, Q.; Li, X.; Dang, J. Fuzzy rough regression with application to wind speed prediction. *Inf. Sci.* **2014**, *282*, 388–400. [CrossRef]
50. Zhou, J.Y.; Shi, J.; Li, G. Fine tuning support vector machines for short-term wind speed forecasting. *Energy Convers. Manag.* **2011**, *52*, 1990–1998. [CrossRef]
51. Kuremoto, T.; Kimura, S.; Kobayashi, K.; Obayashi, M. Time series forecasting using a deep belief network with restricted Boltzmann machines. *Neurocomputing* **2014**, *137*, 47–56. [CrossRef]
52. Wang, H.; Wang, G.; Li, G.; Peng, J.; Liu, Y. Deep belief network based deterministic and probabilistic wind speed forecasting approach. *Appl. Energy* **2016**, *182*, 80–93. [CrossRef]
53. Al-Saudi, K.; Degeler, V.; Medema, M. Energy Consumption Patterns and Load Forecasting with Profiled CNN-LSTM Networks. *Processes* **2021**, *9*, 1870. [CrossRef]
54. Qian, K.; Wang, X.; Yuan, Y. Research on regional short-term power load forecasting model and case analysis. *Processes* **2021**, *9*, 1617. [CrossRef]
55. Raja Santhi, A.; Muthuswamy, P. Industry 5.0 or industry 4.0S? Introduction to industry 4.0 and a peek into the prospective industry 5.0 technologies. *Int. J. Interact. Des. Manuf.* **2023**, *17*, 947–979. [CrossRef]
56. Ramírez-Márquez, C.; Posadas-Paredes, T.; Raya-Tapia, A.Y.; Ponce-Ortega, J.M. Natural Resource Optimization and Sustainability in Society 5.0: A Comprehensive Review. *Resources* **2024**, *13*, 19. [CrossRef]
57. Zota, R.D.; Cîmpeanu, I.A.; Dragomir, D.A.; Lungu, M.A. Practical Approach for Smartand Circular Cities: Chatbots Used in Waste Recycling. *Appl. Sci.* **2024**, *14*, 3060. [CrossRef]
58. Andrade, R.O.; Yoo, S.G. A Comprehensive Study of the Use of LoRa in the Development of Smart Cities. *Appl.Sci.* **2019**, *9*, 4753. [CrossRef]
59. Rozman Cafuta, M. The Sustainability Coefficient of Urban Open Space Illumination Compliance as a Subjective Indicator of Environmental Comfort. *Appl. Sci.* **2024**, *14*, 10375. [CrossRef]
60. Dilawar, N.; Majeed, H.; Beg, M.O.; Ejaz, N.; Muhammad, K.; Mehmood, I.; Nam, Y. Understanding Citizen Issues through Reviews: A Step towards Data Informed Planning in SmartCities. *Appl. Sci.* **2018**, *8*, 1589. [CrossRef]

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