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What can AI reciprocally contribute to energy: concept, method, and technology

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The application of artificial intelligence (AI) has the potential to revolutionize various aspects of human life and industrial production by enhancing efficiency, mitigating human error, and unlocking new avenues for innovation. However, the extensive computational resources demanded by AI consequently lead to substantial energy consumption, presenting a complicated challenge in balancing technological advancement with environmental sustainability. What AI can reciprocally contribute to the energy sector is an intriguing and urgent topic for discussion. This review categorizes the role of AI in terms of its explicit and implicit contributions to the energy sector by summarizing and discussing recent studies on this topic. Explicit contributions rely on the specific and actionable involvement of AI in energy production, including the improvement of energy production efficiency, optimization of renewable energy systems, and enhancement of energy security. In contrast, implicit contributions may not always be apparent but could provide valuable guidance into the energy sector, such as the optimization of energy allocation, promotion of energy conservation, support for sustainable urban development, and advancements in the development of energy materials. Perspectives on future efforts to enhance the contribution of AI to the energy sector are also presented. This review emphasizes the energy-intensive nature of AI technologies and highlights the imperative for strategies to mitigate their environmental impact, suggesting future research directions to achieve a sustainable balance.

artificial intelligence, energy promotion, AI technology in the energy sector, explicit and implicit contributions

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1 Introduction

In the contemporary era characterized by an exponential growth in information volume and a proliferation of fragmented data, the application of artificial intelligence (AI) is instigating substantial transformation and restructuring across diverse industries. Specifically, it has impacted various aspects of individual's lives and industries, including but not limited to healthcare, safety, finance, and industrial sectors at present [1]. The successful implementation of AI heavily relies on extensive computing resources, as they enable intricate calculations and provide essential computational power support for training deep learning models. Taking OpenAI, an AI research company established in the United States, as an example, training a GPT-3XL model with 1.3 billion parameters requires approximately 0.0275 exa floating-point operations per second (EFlops) of computing power per training session [2]. Since the model used for ChatGPT training is a fine-tuned version of GPT-3.5, which also has 1.3 billion parameters, its computational

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demands are similar to those of the GPT-3XL model. Therefore, it can be assumed that training ChatGPT once would require approximately 0.0275 EFlops of computing power. Additionally, assuming ChatGPT undergoes at least 50 training sessions per year, it would require 1.375 EFlops of computing power annually. Considering factors such as input text length, model dimensions, and the number of layers, it can be estimated that each ChatGPT query requires about 2.92×10^{-10} EFlops of computing power. With an estimated 200 million queries per day, ChatGPT would require at least 0.0584 EFlops of computing power daily, resulting in power consumption of approximately 50.22 million kilowatt hours [2].

The extensive computing power requirement will lead to a substantial consumption of energy. Taking Chinese data centers as a case study, energy consumption analysis reveals that power usage primarily stems from information technology (IT) equipment, refrigeration systems, power supply and distribution systems, lighting, and other auxiliary equipment. Electricity costs account for 60%–70% of the total operational expenses. In 2022, the power consumption of all data centers in China is estimated to reach approximately 270 billion kilowatt hours, surpassing the annual power generation capacity of nearly two Three Gorges hydropower stations [3]. Concurrently, the total computing power of data centers in China reached 315 EFlops, encompassing a cumulative count of 85,000 data centers. The average computing power of each data center was 3.7×10^{-3} EFlops, with an annual electricity consumption exceeding 3.177 million kilowatt hours. By analyzing the scale of China's computing power and data center electricity consumption from 2016 to 2021, it can be estimated that the annual electricity consumption required per EFlops ranges approximately between 800 million and 1.2 billion kilowatt hours. Based on the above analysis and projected computational capacity in 2026, it is anticipated that the annual energy consumption of all data centers in China will reach a minimum of 600 billion kilowatt hours by 2026 (Figure 1). The proportion of data center power consumption to China's total electricity consumption is expected to increase from 1.86% in 2016 to ~6.06% by 2026 [4].

Overall, considering both the basic energy consumption in data centers and the future advancements in emerging domains, it is anticipated that the demand for computing resources and electricity usage by AI will persistently increase, potentially exacerbating the energy burden and overall carbon emissions. Therefore, it is imperative for AI to promote the development of the energy industry, alleviate energy pressure, and improve the environment. This review provides a comprehensive overview of recent literature on this subject and classifies AI's role in the energy sector into two categories: the explicit and implicit contributions as summarized in Figure 2. Some typical examples of AI's explicit

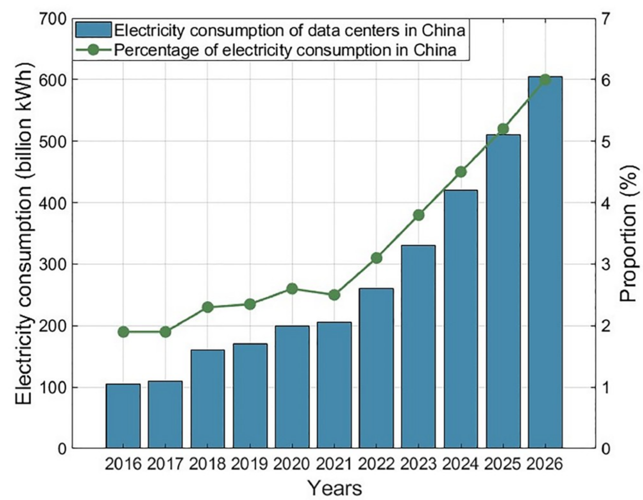

Figure 1 (Color online) Electricity consumption and its proportion in the total national electricity consumption by data centers in China from 2016 to 2026.

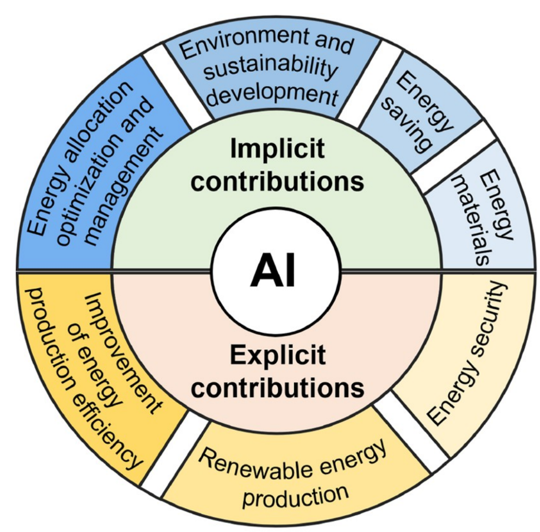

Figure 2 (Color online) A conceptual diagram of AI's contributions to the energy sector.

contributions are illustrated in Figure 3 and Figure 4, while examples of implicit contributions are shown in Figure 5, accompanied by a corresponding discussion in the relevant section. Finally, perspectives on future efforts to enhance the contribution of AI to the energy sector are presented, suggesting research directions aimed at achieving a sustainable balance.

2 The explicit contribution of AI to the energy sector

The explicit contributions of AI to the energy sector refer to its specific and actionable involvement in energy production, with a direct focus on addressing fundamental challenges

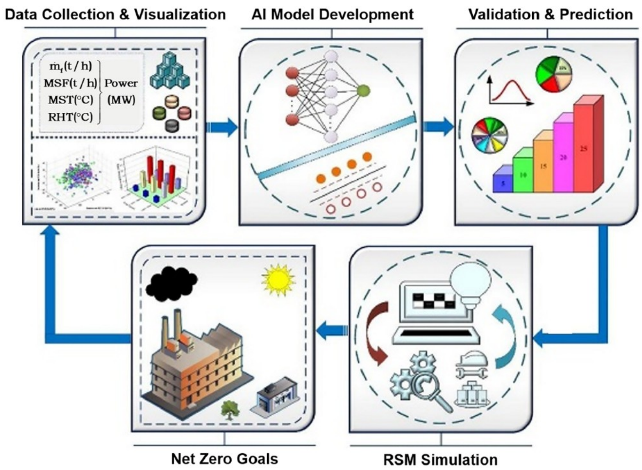

Figure 3 (Color online) An efficient power generation and emission reduction method based on artificial intelligence applied to coal-fired power plants. Reproduced with permission from Ref. [6]. Copyright@2022, Elsevier.

such as enhancing production efficiency, facilitating renewable energy generation, and providing security management.

2.1 AI for improving energy production efficiency

AI technology plays an important role in improving energy production efficiency. Taking thermal power plants as an example, AI technology can facilitate efficient power generation and substantially mitigate carbon emissions through diverse approaches. The architecture of intelligent power generation technology includes three layers: the intelligent device layer, the intelligent operation and maintenance layer, and the intelligent management layer. These layers comprehensively address various aspects ranging from device management to operational optimization. Hua *et al*. [5] demonstrated that AI could optimize combustion processes, improve energy efficiency, and mitigate pollutant emissions through intelligent operations and energy-saving technologies. Muhammad Ashraf *et al*. [6] proposed an efficient power generation and emission reduction method based on artificial intelligence for coal-fired power plants (Figure 3).

In terms of technical applications, successful implementations have been achieved on 300 and 600 MW power generation units using online monitoring technology for the 3D temperature field inside the furnace, as well as precise feedforward control technology for boiler operation optimization based on wind-coal-water independent decoupling and operational data analysis. The implementation of this technology not only reduces coal consumption for power generation but also effectively mitigates the emission of nitrogen oxides from furnace combustion [7]. Furthermore, Zhao *et al*. [8] analyzed the functional design and application of intelligent robot technology in coal-fired smart power plants, encompassing their capabilities to inspect and maintain critical areas such as booster stations, boilers, and turbine rooms, thereby accomplishing the objective of “unmanned operation and few people management”. This technology not only enhances safety measures, but also effectively reduces labor costs and minimizes the occurrence of potential human errors. In addition, the widespread application of automatic control information technology has brought thermal power generation into the era of informatization and networking, which is of great significance for improving power generation efficiency and reducing energy consumption [9]. Lee [10] proposed that intelligent technologies, such as neural networks and fuzzy logic, can be applied to improve the performance of power plants, thereby overcoming unpredictable dynamics and computational complexity issues.

In summary, the application of AI technology enhances the efficiency of power generation in coal-based plants by optimizing the combustion processes, implementing intelligent monitoring and maintenance systems, as well as adopting advanced control algorithms.

2.2 AI for renewable energy production

The application of AI in renewable energy production is extensive and comprehensive, encompassing multiple aspects such as photovoltaic power generation, wind power generation, and hydropower generation.

In photovoltaic systems, AI is primarily employed for addressing challenges such as maximum power point tracking, power generation prediction, and fault detection. Mateo Romero *et al*. [11] revealed that AI can improve the operational efficiency and economic benefits of solar photovoltaic power generation systems through intelligent management and optimization. Kuzlu *et al*. [12] proposed a PV power forecasting methodology using explainable artificial intelligence (XAI) tools (Figure 4a). The integration of photovoltaics and AI has brought about profound transformations in the energy industry, facilitating enhanced utilization of clean and renewable solar energy.

In the field of wind power generation, AI can be applied for various tasks including wind speed and power prediction, optimization control of turbines, and layout optimization of wind farms. Techniques such as artificial neural networks, wavelet neural networks, and hybrid intelligent models can be employed to enhance the accuracy of wind speed and power predictions, thereby facilitating improved management and scheduling of wind power resources within the power system [13]. For example, Qiao *et al*. [14] applied fuzzy logic, genetic algorithm, particle swarm optimization (PSO), and other advanced techniques to optimize the operational status of wind turbines, achieving improved power generation efficiency and stability. Wu *et al*. [15] proposed the utilization of a genetic algorithm and ant colony system

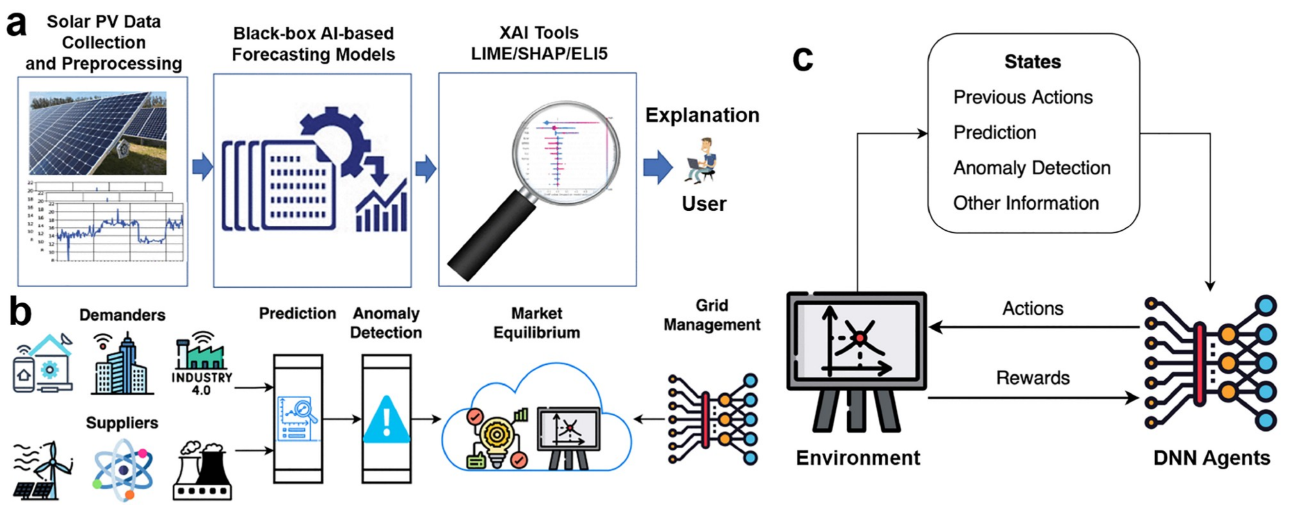

Figure 4 (Color online) The typical cases of explicit contributions. (a) The schematic diagram illustrates a photovoltaic power prediction method using XAI tools. Reproduced with permission from Ref. [12]. Copyright@2020, IEEE. (b) Blueprint of the AI-based electricity grid management system and (c) grid management module. Reproduced with permission from Ref. [19]. Copyright@2023, IEEE.

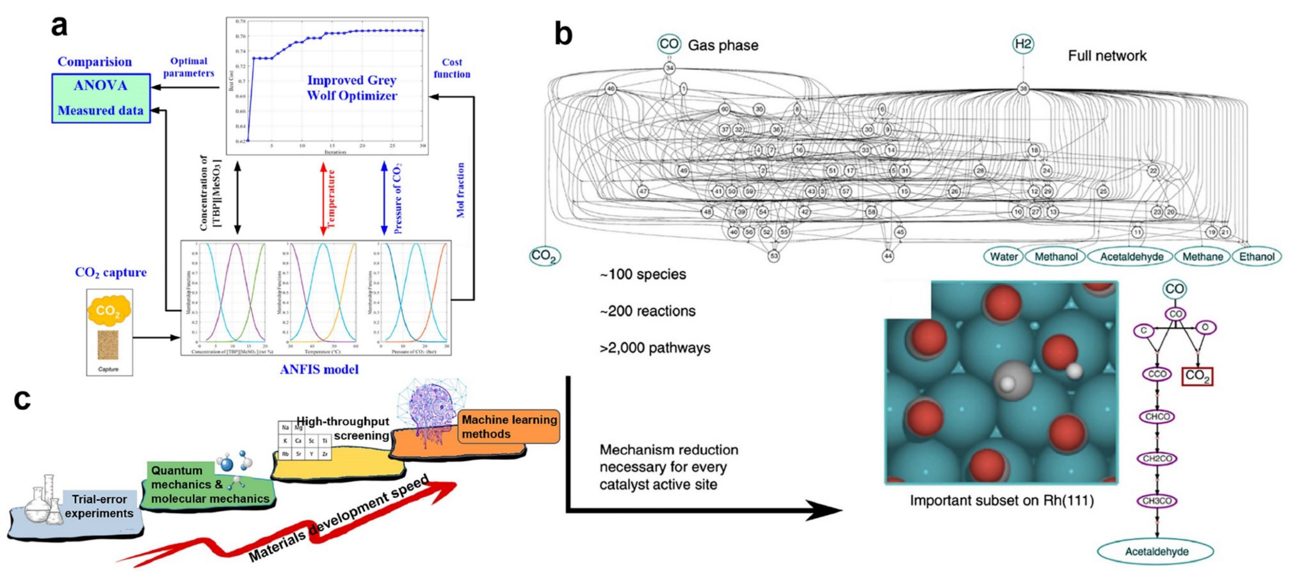

Figure 5 (Color online) The examples of implicit contributions. (a) Improving CO_2 absorption using artificial intelligence and modern optimization for a sustainable environment. Reproduced with permission from Ref. [46]. Copyright@2023, MDPI. (b) Reaction network for the reaction of syngas ($CO+H_2$) to CO_2 and the reduced network for syngas reactivity on Rh(111). The green, gray, red and white balls represent Rh, C, O, and H atoms, respectively. (c) Development in methods to accelerate new materials discovery. Reproduced with permission from Ref. [48]. Copyright@2020, John Wiley and Sons.

algorithm to optimize the layout and transmission system planning of wind farms, aiming to maximize wind power output while minimizing installation and operation costs.

In the field of hydropower, AI is primarily employed for optimizing scheduling, forecasting, monitoring, and maintenance tasks. AI technologies such as machine learning and deep learning can be employed to improve the efficiency and accuracy of hydroelectric power generation. For example, Carvalho *et al*. [16] proposed a new method utilizing artificial neural networks to evaluate future power generation scenarios, facilitating the exploration of the influence of different combinations of power plants on water energy networks. In addition, the integration of AI technology into hydropower plant monitoring systems can significantly enhance operational stability and safety, while concurrently reducing labor costs. Zhao *et al*. [17] proposed an artificial neural network model based on monitoring data to develop an optimized operational system for hydroelectric generating units in hydropower stations.

2.3 AI for energy security

The application and impact of AI in the field of energy security are multifaceted, including smart grid management and optimization, power equipment security management, as well as network security and information protection.

In terms of smart grid management and optimization, AI can enhance the safety of energy production by facilitating fault diagnosis, minimizing power losses, and integrating renewable energy. The faults of the main components in the power grid, such as transformers, lines, and busbars, are diagnosed using AI technologies including back propagation neural network (BPNN) and generalized regression neural network (GRNN) combined with fuzzy decision-making technology. These methods can effectively improve the efficiency of fault handling by operators, thereby enhancing the reliability and safety of power supply in the power system. In power grid regulation, AI technology can provide intelligent decision support, including but not limited to power grid fault identification and load forecasting, thereby enhancing the intelligence level of power grid regulation business [18]. Syu *et al*. [19] proposed a blueprint for the AI-based electricity grid management system (Figure 4b, c). With the rapid deployment of renewable energy sources such as solar and wind, the inherent variability and uncertainties associated with these energy sources amplify the risk of real-time power imbalance in the system. AI technology can enhance the stability and reliability of the power grid by accurately predicting and efficiently scheduling the integration and balance of renewable energy sources with traditional energy. Yang *et al*. [20] proposed an AI system based on deep reinforcement learning, which enables efficient processing of large-scale data sets. This system could assist power grid operators in making scientifically informed and rational decisions to effectively manage electricity fluctuations resulting from renewable energy sources.

In terms of power equipment safety management, an AI-based platform for managing power equipment safety can effectively facilitate the coordination of power equipment resources, standardize communication network timing, and establish a robust operational environment, thereby improving the level of safety management in power equipment [21]. Li [22] employed neural networks and principal component analysis to evaluate the security risks of power system equipment, including the selection of appropriate indicators such as hardware, software, and information system security. Lin [23] proposed an AI-based power grid cloud security protection management system to identify and rectify vulnerabilities in power grid information, thus improving power information security performance. Jiang *et al*. [24] conducted a study on the application of endpoint detection and response (EDR) technology and machine learning algorithms for comprehensive security monitoring and protection of power internet of things (IOT) terminals. Additionally, an intelligent robotic detection system is devised for real-time monitoring of the operational status and meteorological parameters of photovoltaic panels in order to accurately identify equipment faults within photovoltaic power plants. This system could ensure the secure and stable operation of such plants while promoting favorable operational outcomes [25].

In the context of network security and information protection in energy production, AI is playing an increasingly important role. With the development of smart grids, the power system confronts a growing array of network security threats. AI technology can be employed to devise the whole system including design, hybrid power selection, and network security strategies, thereby ensuring sustainable energy production while minimizing pollution or waste generation and reducing operational expenses [26]. The integration of AI and machine learning technologies can substantially elevate the level of network security in the power industry as demonstrated by Mohamed *et al*. [27]. Meanwhile, AI technology excels in the identification and defense against network attacks. For example, Huang [28] has further developed strategies based on AI to enhance the information security prevention and control system of power grid enterprises.

3 The implicit contribution of AI to the energy sector

The implicit contributions of AI may not always be apparent but could provide valuable guidance in the energy sector, such as the optimization of energy allocation, promotion of energy conservation, support for sustainable urban development and innovating material design.

3.1 AI for energy allocation optimization and management

By utilizing AI algorithms, efficient management and scheduling of distributed energy resources such as electric vehicles and energy storage batteries can be accomplished, ensuring dependable energy allocation. Furthermore, AI can optimize the operation status of the power grid, and reduce faults and losses by enabling real-time monitoring and analysis.

The digitalization and intelligence of urban energy systems are continuously advancing, with edge intelligence technology serving as a crucial component in supporting distributed resources within these systems. By leveraging cloud-edge collaboration and mechanism design, edge intelligence technology can improve the operational efficiency and response speed of energy systems [29]. Ruan *et al*. [30] proposed a method for optimizing the operation of distributed energy systems using deep reinforcement learning, enabling real-time optimization through distributed proximal policy optimization (DPPO). Zhou *et al*. [31] proposed a real-time automatic optimization scheduling strategy based on the K-means clustering algorithm and long short-term memory neural network (LSTM) to optimize the charging and discharging of electric vehicles connected to the network. This strategy can effectively generate an approximate optimal solution within milliseconds, independent of users' precise travel time inputs, making it well-suited for real-time optimization and scheduling of electric vehicles on a large scale [31].

3.2 AI for energy conservation

The application and impact of AI in energy conservation are multifaceted, including direct reduction of carbon emissions by improved energy efficiency, as well as indirect achievement of sustainable development by optimizing the design and management of energy systems. However, it is crucial to consider the substantial energy consumption associated with AI itself.

Firstly, AI technology has significant potential to improve energy efficiency through intelligently predicting and optimizing energy consumption, thereby mitigating wastage and improving overall efficiency [32]. Specifically, Yang *et al*. [33] demonstrated that the integration of AI's computational intelligence, perceptual intelligence, and cognitive intelligence, can effectively change traditional energy utilization patterns, thus further promoting intelligent capabilities within power systems and integrated energy systems. Zhang *et al*. [34] demonstrated that the implementation of machine learning and other artificial intelligence algorithms can enhance the identification, detection, and classification of power quality issues, enabling more effective measures for optimization and adjustment to improve energy utilization efficiency. Furthermore, AI can also be used to predict and regulate energy usage in buildings, thereby mitigating unnecessary energy consumption. By employing artificial neural networks, it is possible to predict and optimize the heat loss of buildings. Khedher *et al*. [35] utilized a hybrid approach combining PSO and harmony search (HS) algorithms, along with multilayer perceptron (MLP), to forecast the heat loss of buildings based on the thermal conductivity coefficients of walls and coating materials, as well as indoor and outdoor surface temperatures. The performance and prediction accuracy of this model were evaluated using the coefficient of determination (R^2) and root mean square error (RMSE), revealing exceptional results in terms of precision. Xie [36] found that the application of machine learning algorithms in predicting building energy consumption, forecasting building loads, and evaluating comprehensive energy-saving technologies can enhance the efficiency of energy-efficient building design and research on energy consumption. Morina *et al*. [37] utilized machine learning algorithms, thermal imaging technology, and IoT sensors to optimize energy consumption in smart homes. These technologies not only contribute to the improvement of energy efficiency, but also facilitate waste reduction and ensure optimal user comfort. Bagheri *et al*. [38] proposed a method for sharing computing and data storage resources, which can lead to substantial energy savings in various building types, regardless of their functionality, classification, or heating system.

Additionally, AI has the potential to enhance its energy efficiency through advancements in hardware architecture and software optimization techniques. In terms of hardware design, dedicated accelerators can be developed based on the inherent characteristics of deep learning models, such as using FPGA or GPU for optimization. This method can enhance hardware performance while simultaneously reducing the computational requirements on the algorithmic side. Shafik *et al*. [39] utilized the Tsetlin machine learning algorithm based on the principle of finite state automata for resource-efficient hardware design. This algorithm operates on natural logic rather than arithmetic operations, thereby enabling a significant reduction in energy consumption while maintaining high learning efficiency. In terms of software, Zhao *et al*. [40] found that employing techniques such as instruction-level optimization, algorithm-level optimization, and software architecture optimization can effectively mitigate redundant computation and data transmission, thus reducing the overall energy consumption of AI systems. He *et al*. [41] simplified the training process of deep neural networks by introducing a residual learning framework, facilitating network depth without significantly augmenting training complexity. In addition, employing techniques such as knowledge distillation enables the compression of intricate models into more lightweight versions to accommodate the resource constraints of edge devices [42]. Yan *et al*. [43] utilized AI technologies, including deep learning and deep reinforcement learning, for energy management and optimization in cloud computing data centers. These technologies can facilitate the attainment of cross-layer awareness regarding data center energy consumption and enable precise management of energy, thereby improving energy efficiency and mitigating environmental impact. Besides, Kelechi *et al*. [44] found that AI can improve the energy efficiency of high-performance computing (HPC) entities by continuously monitoring power consumption across all components and leveraging data in a database to optimize and automate processes.

3.3 AI for environmental and sustainable development

The application and impact of AI in sustainable development and carbon reduction are also multifaceted. Specifically, the application of AI in urban planning and management plays a crucial role in achieving sustainable urban development goals (SDGs). By applying AI technology, more effective implementation of waste management, air quality monitoring, disaster response management, and traffic management can be achieved, thereby enhancing cities' sustainability and residents' quality of life. The utilization of AI technology in environmental monitoring and protection also exhibits significant potential. For example, AI can effectively forecast and monitor greenhouse gas emissions, providing valuable support in mitigating global warming. Notably, the study by Nassef *et al*. [45] demonstrated that AI technology can accurately predict carbon dioxide emissions, providing precise data support for policy makers to make well-informed decisions. Meanwhile, they also utilized artificial intelligence and modern optimization technology to improve the carbon dioxide absorption rate for sustainable development (Figure 5a) [46]. In addition, Zhu *et al*. [47] proposed that AI can also be employed for urban-level carbon peak and carbon neutrality planning and governance, thereby supporting national spatial planning through the analysis of the correlation between urban spatial form evolution and carbon emissions.

3.4 AI for energy materials

The application of AI in the field of energy materials is progressively changing the traditional model for material research and development, providing novel prospects to address global energy challenges through improving efficiency, reducing costs, and promoting innovation. Chen *et al*. [48] summarized several stages of material development and found that machine learning could also be used to study reaction mechanisms by reducing the complexity of reaction networks, thereby accelerating the development of energy storage and conversion materials (Figure 5b, c). Besides, Maleki *et al*. [49] proposed a machine learning-based method for predicting and optimizing the performance of new materials by analyzing extensive datasets, facilitating the discovery and development of new materials with tailored properties in a shorter period of time. This method accelerates the development process of energy materials. AI has the potential to improve the efficiency of material design and reduce experimental costs and time by learning historical data and experimental results. In the field of energy conversion and storage, such as batteries, super capacitors, and photocatalysts, the application of AI can facilitate the optimization of the microstructure and composition of these materials to achieve higher energy conversion efficiency and longer service life [50].

4 Summary and outlook

This review highlights the transformative impact of AI on the energy sector, emphasizing both explicit and implicit contributions. AI has been shown to significantly enhance energy production efficiency, optimize renewable energy systems, and contribute to the development of innovative energy materials. These advances have enabled industries to reduce carbon emissions, improve energy utilization, and transition towards cleaner energy solutions. However, the growing energy demands associated with AI technologies pose significant challenges. To harness the full potential of AI in the energy industry while minimizing its environmental footprint, future research directions can include the following three aspects.

(1) The application of AI in energy policy-making. The application of AI technology in the energy policy-making process is an emerging field. By leveraging big data analysis and machine learning techniques, AI has the capability to simulate and predict the potential impact of different energy policies, optimize the energy pricing system, and effectively manage fluctuations in supply and demand within the market. In addition, AI can facilitate policy makers in accurately evaluating the long-term impacts of measures such as carbon taxes and renewable energy subsidies, thereby enhancing the transparency and efficiency of the energy market. However, the comprehensive exploration of AI technology's potential in optimizing the decision-making process, implementation management, and execution stages of energy policies, as well as ensuring the substantive fulfillment of energy system demands, remains an area that requires further research [51].

(2) The application of AI in waste heat recovery and utilization. A significant proportion of energy in industrial energy systems is dissipated as waste heat. In the future, AI can optimize waste heat recovery systems, enabling real-time monitoring and management of the process while assisting industrial facilities in maximizing waste heat utilization for enhanced energy efficiency. Currently, the application research in this field is fragmented and lacks a comprehensive framework [52].

(3) The application expansion of AI in the field of nuclear energy. Nuclear energy is a low-carbon energy source; however, ensuring its safety and effective operational management presents intricate challenges. In the future, the application of AI in the field of nuclear energy can significantly enhance the safety monitoring and risk prediction capabilities within nuclear power plants. AI could enable the real-time analysis of data, facilitating the identification and prevention of potential equipment failures, radiation leaks, or other safety hazards, thus effectively mitigating the occurrence of accidents. Additionally, AI can aid in the processing and management of nuclear waste, optimize waste disposal procedures, and ensure the attainment of environmental safety standards [53]. Furthermore, AI has the potential to accelerate the advancement of nuclear fusion technology. By facilitating the analysis of extensive data in nuclear reactions and establishing predictive models, it enables scientists to

gain insights into and optimize the intricate process of nuclear fusion reactions [54].

In conclusion, while AI offers profound opportunities for the energy sector, its sustainable growth must be aligned with environmentally conscious practices. A comprehensive approach that addresses both technological advancements and environmental challenges is imperative to ensure that AI can effectively drive the transformation of the energy industry in a sustainable manner.

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