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Emerging information and communication technologies for smart energy systems and renewable transition

Ning Zhao [a], Haoran Zhang [b], Xiaohu Yang [c], Jinyue Yan [d,e,*], Fengqi You [a,f,*]

[a] Systems Engineering, Cornell University, Ithaca, NY, 14853, USA
[b] School of Urban Planning and Design, Peking University, Shenzhen, 100871, China
[c] Institute of the Building Environment & Sustainability Technology, School of Human Settlements and Civil Engineering, Xi'an Jiaotong University, Xi'an, 710049, China
[d] Future Energy Center, Malardalen University, Sweden
[e] Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Hong Kong
[f] Robert Frederick Smith School of Chemical and Biomolecular Engineering, Cornell University, Ithaca, New York, 14853, USA

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ABSTRACT

Since the energy sector is the dominant contributor to global greenhouse gas emissions, the decarbonization of energy systems is crucial for climate change mitigation. Two major challenges of energy systems decarbonization are renewable transition planning and sustainable systems operations. To address the challenges, incorporating emerging information and communication technologies can facilitate both the design and operations of future smart energy systems with high penetrations of renewable energy and decentralized structures. The present work provides a comprehensive overview of the applicability of emerging information and communication technologies in renewable transition and smart energy systems, including artificial intelligence, quantum computing, blockchain, next-generation communication technologies, and the metaverse. Relevant research directions are introduced through reviewing existing literature. This review concludes with a discussion of the industrial use cases and demonstrations of smart energy technologies.

1. Introduction

The transition from conventional carbon-intensive energy systems to renewable and smart energy systems is crucial for global decarbonization and climate change mitigation, as the energy sector is the dominant contributor to global greenhouse gas emissions [1]. Two main categories of problems associated with achieving decarbonized energy systems are energy transition planning [2] and sustainable systems operations [3]. Energy transition design aims to plan for the capacity changes of energy production, storage, and electricity transmission, and the planning decisions generally have long time intervals on a yearly basis. For operations, reliability and flexibility are crucial for smart energy systems that merge electricity, heating, and transportation sectors, while addressing the fluctuations and uncertainties from both the demand and supply sides on intra-hour, hourly, daily, and seasonal time scales. To facilitate energy systems decarbonization, it would significantly benefit the planning of energy transition and the operations of smart energy systems to harness emerging technologies, such as artificial intelligence (AI), quantum computing, blockchain, next-generation communication technologies, and the metaverse, as demonstrated by academic studies and industrial applications (see Fig. 1).

Incorporating emerging technologies in energy transition and smart energy systems has been investigated extensively in academic research. AI-based tools, including optimization [4], sequence-to-sequence learning [5], federated learning [6], computer vision [7], and explainable AI [8], have demonstrated their applicability for addressing complex problems in smart energy systems with high accuracy and computational efficiency. Quantum computing has presented remarkable computational performances for certain intractable tasks for conventional devices, which provides an innovative tool for solving the highly complex design and operations problems in future decarbonized smart energy systems [9], and support the decarbonization goals by country (see Fig. 2). Because decentralized energy production is projected to play an important role in smart energy systems, more sophisticated mechanisms are required to track the trading activities among various energy providers and consumers, and blockchain technology presents a potential approach to track the complex trades in energy systems democratically and automatically without a central authority. Advances in wireless communication technologies, such as state-of-the-art fifth-generation (5 G) and future sixth-generation (6 G) wireless networks, facilitate the effective coordination of operations in smart energy systems and help address the increasing complexity of the energy systems

* Corresponding authors.
E-mail addresses: jinyue.yan@mdu.se (J. Yan), fengqi.you@cornell.edu (F. You).

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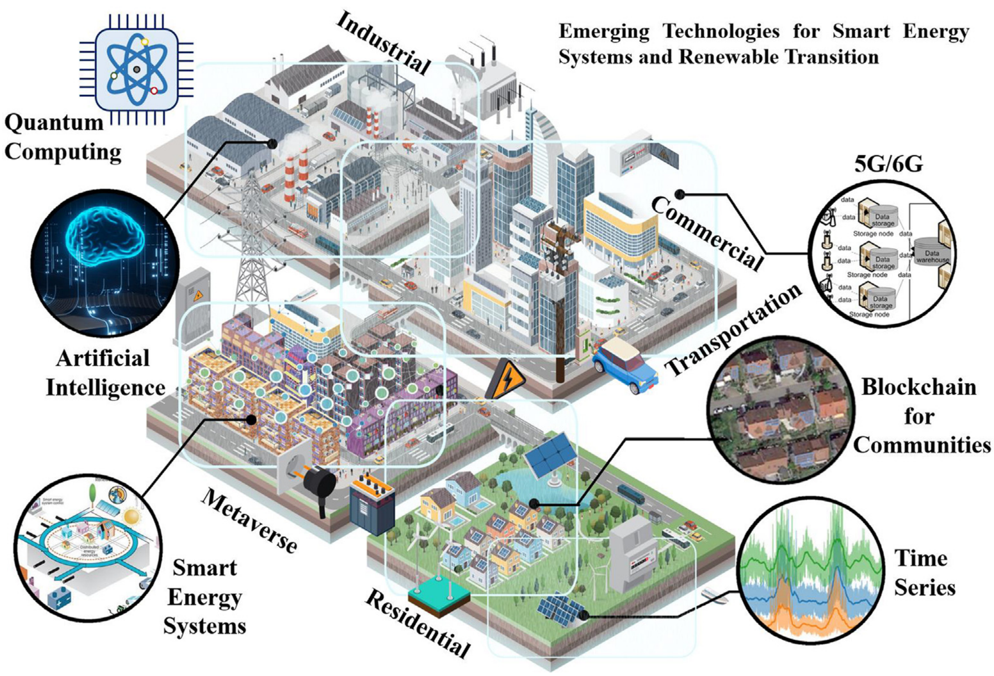

Fig. 1. Emerging technologies for smart energy systems and renewable transition, including artificial intelligence (AI), quantum computing, blockchain, fifth-generation (5 G) and future sixth-generation (6 G) wireless networks, and the metaverse.

associated with the growing penetration of renewable energy. The expanding metaverse sector would also have significant impacts on the planning and operations of future energy systems in the coming decades, owing to its displacement impacts on a wide range of real-world energy-consuming activities. The extensive academic research studies focusing on the integration of emerging computing, information, and communication technologies with renewable transition and smart energy systems operations have incited industrial demonstrations and use cases [10]. For instance, AI-based technologies have been practically adopted to address complex problems for the design and operations of smart energy systems [11], and blockchain technology has demonstrated its effectiveness in recording trading activities in multiple microgrids [12]. The objective of this study is to review the recent academic findings and industrial applications of emerging information and communication technologies in smart energy systems and renewable transition. To achieve this goal, this paper aims to provide insights into the following three important questions:

- What are the state-of-the-art research studies incorporating emerging information and communication technologies in energy transition and smart energy systems?
- How does each of the emerging technologies effectively facilitate the planning of renewable transition and the systems operations?
- What are the industrial demonstrations and use cases for the adoption of computing, information, and communication technologies with energy systems decarbonization and operations?

The remainder of this article is organized as follows. Sections 2 focuses on using quantum computing, blockchain, 5 G/6 G, and the metaverse in the design and operations of future energy systems. Section 3 introduces AI-based technologies on energy systems decarbonization, including optimization, time series and sequence-to-sequence learning, federated learning, computer vision, and explainable and trustworthy AI. Use cases and industrial demonstration examples are discussed in

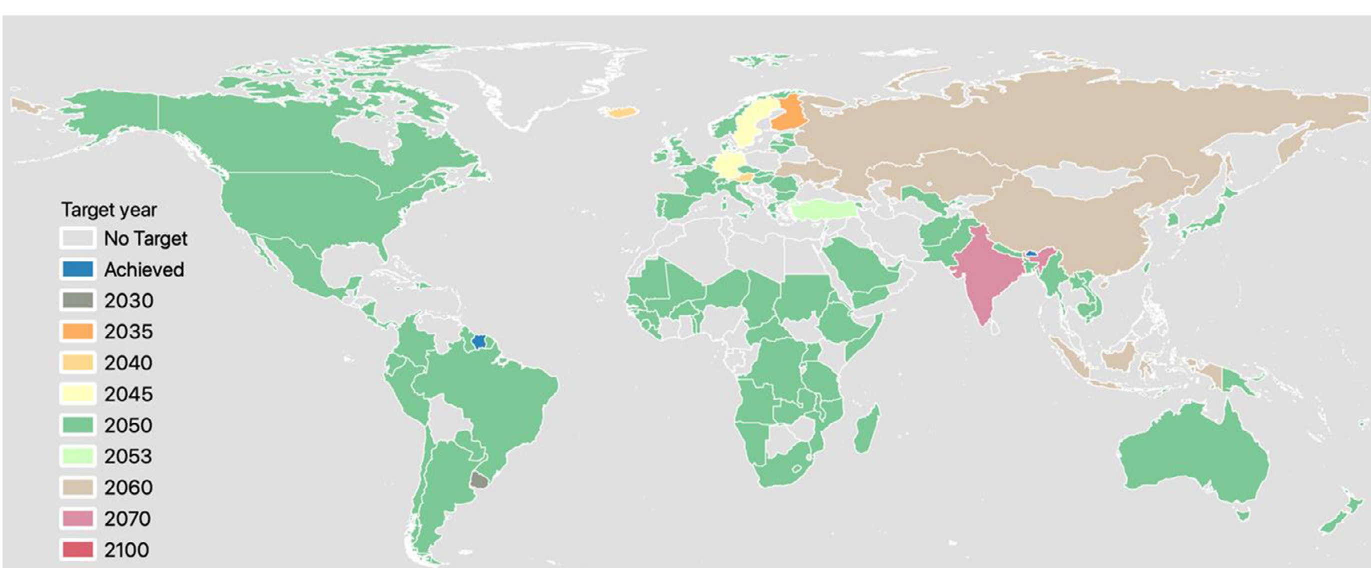

Fig. 2. Decarbonization goals by country or region in terms of the target year for achieving net zero carbon emissions and the pledges of decarbonization.

Section 4. Outlook and conclusions are summarized in Sections 5 and 6, respectively.

2. Non-AI emerging information and communication technologies for smart energy systems and renewable transition

2.1. Quantum computing for smart energy systems and climate neutrality

2.1.1. Quantum computing

Quantum computing has demonstrated its exceptional computational performance for certain tasks that are intractable even for supercomputers, and this advantage can benefit the design and operations of future smart energy systems [9]. The advantages of quantum computing are realized mainly because of its ability to harness the phenomena of quantum mechanics, which leads to different computational operations compared to classical computers [13]. Specifically, classical computing stores data using bits that are represented by discrete values of either 0 or 1, while quantum computing manages information in quantum bits (qubits), which live in a superposition of the 1 and 0 states. Quantum algorithms described by a quantum circuit acting on a set of qubits are required to exploit quantum computing to address problems in the physical world [14]. For instance, quantum computing has been utilized in multiple engineering applications associated with sustainable development, including energy systems optimization [15], biomass mix selection [16], and sustainable production planning [17]. Furthermore, researchers have implemented quantum computing in multiple types of smart energy systems applications [18], including electric grid operations [19], energy storage [20], power dispatch [21], and load forecasting [22].

Considering the extensive adoption of AI in the energy sector, integrating quantum computing with AI has the potential to improve energy systems design and operations. Two main branches of quantum AI for smart energy systems applications are quantum machine learning and quantum-enhanced optimization, which will be discussed in the following subsections.

2.1.2. Quantum-enhanced optimization

Quantum-enhanced optimization may bring improved computational efficiency compared to conventional optimization on classical computers. Optimization problems exist in various areas of the energy systems design and operations [23], but it should be noted that the optimization of the deep-decarbonized smart energy systems tends to be NP-hard in multiple problems [24], indicating that the computational complexity will significantly increase for large-scale applications using classical computers. In comparison, quantum computers can assist with addressing this issue by adopting quantum algorithms with computational efficiency improvements compared to the best-performing classical approaches. It is worth noting that such computational advantages of quantum optimization algorithms are typically observed for certain classes of optimization problems, and they are not general enough to handle all types of mathematical programming problems [25].

Quantum-enhanced optimization may result in computational speedups for the design and operations of smart energy systems, in terms of renewable energy supply networks, energy infrastructure design, and electric power distribution. The quantum-enhanced optimization approaches for smart energy systems are divided into two categories, namely binary optimization and continuous optimization. Binary optimization problems incorporate variables from the sets of $\{-1, 1\}$ or $\{0, 1\}$, and quantum computers are capable of solving binary unconstrained optimization problems with quadratic objectives, namely quadratic unconstrained binary optimization (QUBO) problems [26]. As QUBO models are general enough to adapt to multiple types of constrained and unconstrained problems [27], such flexibility offers valuable opportunities to tackle the mathematical programming problems in smart energy systems with a quantum-enhanced optimization approach. As for continuous optimization, significant polynomial speedups are observed for using the quantum interior point method to solve general quadratic programming (QP), linear programming (LP) and semidefinite programming (SDP) problems [28], by means of applying the KKT conditions, Lagrange multipliers, and the Harrow-Hassidim-Lloyd (HHL) quantum algorithm [29]. Therefore, the planning and operations problems for smart energy systems formulated as QP, LP, and SDP can take advantage of the computational efficiency improvements provided by quantum-enhanced optimization, such as power dispatch [30], electric vehicle charging schedules [31], and microgrid operations with demand response [32].

2.1.3. Quantum machine learning

Quantum machine learning is capable of addressing multiple drawbacks of the existing machine learning approaches achieved on classical devices, which provides potential advantages for application in smart energy systems. Machine learning has been extensively applied to the design, model, and operations of smart energy systems [33]. Still, there may exist disadvantages for large-scale applications in the physical world, in terms of scalability and computational complexity [34]. To tackle these drawbacks, exploiting quantum computers in machine learning tasks can benefit increasing computational efficiency, which helps to improve the application of machine learning-based approaches in real-world energy transition and smart energy systems.

Quantum machine learning has been adopted for various categories of machine learning tasks, including supervised learning, unsupervised learning, and reinforcement learning, suggesting that the machine learning-based approaches in smart energy systems may benefit from the integration of quantum computing [35]. The speedups of quantum machine learning can be achieved by using quantum computing to improve the computational performances for multiple components of machine learning algorithms, such as matrix operations on vectors in high-dimensional vector spaces, classification accuracy, and sampling of classically inaccessible systems [35]. In other words, it is crucial to benefit from quantum machine learning to specify certain tasks with computational advantages while performing on quantum computers. Therefore, quantum computing has the potential to address the computational complexity resulted from using machine learning techniques in smart energy systems, including supervised, unsupervised, and reinforcement learning. For instance, supervised learning has demonstrated applicability in electricity price forecasting [36], electricity storage control [37], and energy demand prediction [38], among others. Unsupervised learning has been applied to energy transition planning under uncertainty [39], energy demand representation [40], and time series electricity data analysis [41]. As for reinforcement learning, researchers have adopted the techniques for energy systems design [42] and operations [43].

2.2. Blockchain for smart energy systems

With the increasing penetration of variable renewable energy and the rising of electricity prosumers, smart energy systems are projected to become more complex and decentralized in the future [44], and blockchain technology can help with operations management for such energy systems [45]. Blockchains, or **distributed ledger technologies (DLT)**, aim to facilitate distributed transactions by removing central management. A blockchain is a continuously growing list of records, namely blocks, which are linked and secured based on cryptography. To form a chain of blocks, each block or record contains a hash of the previous block using cryptography, the transaction data, and a timestamp that proves the existence of the transaction data when creating the block. As each block includes information from the block before it in the form of a cryptography hash, the blocks effectively build a chain of records by linking each additional block with its previous one. The decentralization of a blockchain is enabled by sharing the list of records among a network of nodes, and each node is a computer that has an exact replica of the blockchain, which ensures that the transaction data in the blockchain cannot be altered or deleted without the control of more than half of the network [46]. There are various types of blockchain applications in smart energy systems, such as energy management in smart grids and peer-to-peer (P2P) energy trading. Meanwhile, the significant energy impacts of blockchain technology also draw attention from the perspective of sustainability.

Blockchain technology provides a collaborative mechanism that is capable of managing energy systems operations democratically and automatically in the absence of a central authority, in order to overcome the challenges resulted from the distributed structure of the smart energy systems [47]. Based on blockchain technology, new mechanisms and platforms for energy trading have been developed and implemented at various levels between generators, suppliers, traders, end-users, and prosumers [48]. At the wholesale level, energy trading takes place between generators, suppliers, and traders, and blockchain-based platforms have been developed and tested in the real world, such as the Enerchain framework in Europe developed by PONTON [49]. It is important for the smooth operation of smart energy systems to address the cooperation between different energy systems participants without a central authority. Multiple frameworks have been developed to address this issue, such as using smart contracts [50], the Stackelberg game [51], the consortium-blockchain consensus mechanism [52], and the Proof of Solution mechanism based on mathematical programming [53]. For energy retailers or microgrids, blockchain technology assists energy trading in terms of improving demand side management [54], incorporating prosumers through P2P trading [55], and microgrid control [56].

The impacts of blockchain technology on energy systems also attracted attention from both academia and the industry. For instance, bitcoin, a well-known blockchain example, has consumed more energy than a number of countries in recent years [57]. It is also found that the average energy consumption of bitcoin mining is higher than that of mineral mining (except for Aluminum mining) to produce an equivalent market value [58]. The booming mining activities of bitcoin and other cryptocurrencies require increasing energy consumption in this field, which expectedly leads to growing greenhouse gas (GHG) emissions. Researchers estimated that bitcoin mining resulted in around 23 and 90 Mt CO_2 in 2018 [59] and 2021 [60], respectively. Consequently, the increasing mining activities of cryptocurrency will negatively affect climate change mitigation, and it is projected that bitcoin-induced emissions along could push global warming above 2 °C before the middle of this century [61]. To alleviate the energy and environmental concerns of bitcoin, Niaz et al. have proposed a framework using bitcoin mining to mitigate wind and solar curtailments, which addresses the sustainability issue of bitcoin and generates profits from renewable electricity curtailment [62]. The environmental concerns for bitcoin mining can also be alleviated by incorporating carbon capture and renewable energy, by taking advantage of the profitability of bitcoin, the sustainability benefits of carbon capture, and the carbon neutrality of renewable energy [63]. It is worth noting that the energy consumption and environmental impacts of blockchain technology can be reduced by changing the consensus mechanism. For instance, the proof-of-work mechanism of bitcoin is the major cause of its high electricity consumption. In comparison, Ethereum, the second largest cryptocurrency, switched its consensus mechanism from proof-of-work to proof-of-stake in 2022, which requires no energy-intensive computational process for sustaining the blockchain and is projected to reduce electricity consumption by 99.95% [64].

2.3. 5G and 6G for smart energy systems

Wireless communication technologies have kept improving during the past decades, and state-of-the-art 5 G and future 6 G wireless networks can facilitate the efficient management of smart energy systems [65]. With the increasing complexity of the energy systems owing to the high penetration of renewable energy and growing variety of demands, the communication technologies that coordinate the operations of energy systems participants are becoming more and more important for energy systems reliability [66]. The latest commercialized mobile communication technology is 5 G, which has data rates of up to 20 Gbps and latencies of around 1–10 ms. The advances provided by 5 G have benefited a variety of applications in smart energy systems, such as demand response (DR.), decentralized solution algorithms, and information exchange for renewable electricity generation. In terms of future development of the next generation of wireless networks, 6 G is projected to boost the data rate by 10–100 times to 1 Tbps [67], lower the latency to less than 0.1 ms [68], improve the reliability to 9-nines [69], and increase the coverage [70]. Such improvements allow 6 G to provide ultra-reliable low latency communications (URLLC) services, enabling the realization of reliable smart grid operations, safe vehicular networks, remote equipment monitoring, and ultra-fast energy trading using blockchain [65].

The recent advances in communication technologies have benefited the management of smart energy systems, as 5 G has been studied and implemented for various functions in energy systems. Examples include increasing the reliability of power systems, enhancing the security of smart grids, and assisting energy management in smart buildings. Specifically, 5 G can effectively support communications in smart grids, as a massive volume of data is required to be collected, exchanged, and processed for the analysis and guidance of systems operations and services [71]. The real-time accessibility of energy-related data from both the demand and supply side is crucial for complex smart energy systems that accommodate distributed energy resources (DER) [72] and the IoT [73]. To address the information exchange issues, the high bandwidth, high capacity, and low latency features of 5 G have demonstrated potential applicability in the communications between a variety of participants in smart grids, such as market operators, system operators, energy service companies, computing resources, and grid users [74]. The reliability, efficiency, and security of power systems can be improved by 5 G wireless communication technology, through real-time energy data analytics [75], edge computing [76], and demand response [77]. In addition to the application at the grid level, 5 G also benefits energy management at smaller scales, like smart buildings [78], owing to the massive high-quality data on energy consumption and demand prediction for IoT devices and distributed subsystems that are exchanged through the connection with 5 G wireless networks [79].

The next-generation 6 G wireless networks will provide improved services and support for the operations of smart energy systems, due to its features of higher data rates, lower latency, and better heterogeneous connectivity [80]. As 6 G can achieve fast communication with improved data rates, latency, and reliability compared to 5 G, it is forecasted to alleviate communications issues between a variety of smart grid components. Such connectivity improvements of 6 G also enable multiple types of operational improvements for smart energy systems [65], including P2P energy trading, smart metering for prosumers and consumers, real-time pricing, optimal systems operations, AI-assisted renewable power generation prediction, and electric vehicle management [81]. Furthermore, 6 G wireless networks are projected to provide more scalable and heterogeneous connections compared to 5 G [82], enabling space-air-ground integrated networks that aim to realize a digitalized and linked world that is not feasible with 5 G communication technologies [83]. Expectedly, the connections of 6 G would be faster and more sophisticated than the existing satellite-based networks such as Starlink [84]. Thus, numerous devices in the real world are connected through 6 G networks, achieving seamless interaction between various types of equipment [85], which provides the foundation for accurate real-time monitoring and operating of smart energy systems. The huge amounts of interconnected devices through 6 G networks raise concerns about their energy consumption, as a large proportion of devices could be wireless and mobile, and energy harvesting may become a promising solution for addressing this issue [86]. 6 G wireless system is also expected to play an important role in the booming of the metaverse industry [87], which is projected to have significant impacts on the energy sector and the environment, as discussed in the following section.

2.4. Metaverse for smart energy systems and climate change mitigation

The **metaverse** is a large network of interconnected 3D immersive digital worlds [88], constructed by harnessing the technology advances in Web 3.0 [89], blockchain [90], virtual reality (VR) [91], and augmented reality (AR) [91]. The metaverse technology is projected to infiltrate all economic sectors with the potential of growing into a billion-user sector [92], and it is estimated that the market opportunity of the metaverse can exceed $1 trillion in terms of global annual revenues [93]. The projected rapid growth of the metaverse industry can result in significant and profound changes to socioeconomic activities, as the metaverse provides a seamless convergence of physical and digital lives where people can work, entertain, relax, educate, and communicate.

The growth and experience of the metaverse depend on the performance improvement and economic efficiency of multiple key technologies, including VR, AR, Web 3.0, and non-fungible tokens (NFTs). One of the key features of the metaverse experience is that every user is placed inside a virtual 3D world and connected with other users via the internet. Since it is difficult to achieve such a virtual experience on conventional screen-based devices, such as smartphones and tablets, VR or AR tends to be a preferable way to experience a 3D world or space in an immersive manner [94]. Furthermore, there are also additional technologies like haptic feedback that can further improve the human-machine interface for VR and AR applications in the metaverse [95]. In order to exchange information between different users or virtual worlds, Web 3.0, the new iteration of the World Wide Web that incorporates the idea of decentralization, can help set up connection rules for the metaverse [96]. The decentralized feature of Web 3.0 allows the operations of metaverse-based virtual worlds in absence of a group of centralized technology companies that are often referred to as "Big Tech" in the age of Web 2.0 [97]. Along with the trend of decentralization in Web 3.0, the economic activities in the metaverse should also adapt to blockchain-based systems for finance management that complete transactions in a P2P manner without a trusted third party, such as decentralized finance (DeFi) [98] and NFT [99]. Considering that each NFT is unique and tradable, it can serve as a tool to support virtual markets for various types of assets, including collectibles, art works, and real estate based on virtual territory [100].

The booming metaverse sector would have considerable impacts on the design and operations of smart energy systems in the coming decades, which can consequently affect environmental sustainability on a large scale. Specifically, the increasing activities on the metaverse-based applications, such as virtual working, learning, and traveling, will correspondingly reduce the activities of their real-world counterparts, including on-site working, in-person learning, and tourism in the physical world. As the metaverse growth can relocate a series of in-person activities, it is expected that less energy would be required for commercial and industrial activities if their metaverse alternatives exist, and such digitalization impacts will lead to reduced transportation demand, energy, and emissions. On the other hand, the expansion of the metaverse can increase the energy demand from metaverse-dependent equipment and the time of residential staying, which results in more energy consumption at the residence and from electronic devices. Therefore, the overall impacts of the metaverse on energy, environment, and climate change should be further investigated to uncover the optimal planning and operations of future smart energy systems for accommodating the metaverse expansion.

3. AI for smart energy systems and renewable transition

AI is projected to play an important role in the design of energy transition and operations of smart energy systems, because it provides innovative tools that address complex problems in the energy sector with remarkable accuracy and high computational efficiency. For instance, deep learning for optimization can learn the load change trends from historical data and achieve state-of-the-art performances in predicting future loads accordingly with exceptional accuracy [101]. AI-based approaches also facilitate the secure operation of smart energy systems [102] and the effective detection of dynamic attacks [103]. Furthermore, time series and sequence-to-sequence learning emerge as promising tools to be embedded in smart sensors, which provide cost-effective and scalable solutions to break down energy consumption at a small scale and make a reliable forecast for smart energy systems [104]. In addition, advanced AI-based methods that have demonstrated applicability and effectiveness in smart energy systems, including federated learning, computer vision, explainable AI, and trustworthy AI, are also discussed in this section.

3.1. Optimization in AI and applications in energy systems

AI, including deep learning, is a powerful tool for the optimization of smart energy systems. One of the characteristics of deep learning is the massive amount of data, so improving the computational efficiency of deep learning is important for energy systems applications. To this end, optimization with the gradient descent method in machine learning aims to find a local minimum of a given cost function by finding the preferable or optimal values of the corresponding parameters (coefficients). The process operates in an iterative manner that consists of two steps, namely calculating the gradient of the cost function and moving toward the direction opposite to the gradient. Furthermore, mathematical programming-based deterministic optimization also demonstrates extensive applicability across a wide range of energy systems design and operations problems. Generally, such optimization approaches construct mathematical models for targeting problems in the energy sector, which minimize or maximize the objective functions by adjusting the values of decision variables under a set of inequality constraints. Typical objective functions for computational optimization include cost minimization, profit maximization, and social welfare maximization. In energy systems optimization, decision variables can reflect the long-term systems planning or short-term operations decisions, and the constraints represent the conditions that must hold under the optimal values of decision variables.

Optimization has demonstrated its applicability and effectiveness in designing energy transition pathways. Electrification and decarbonization of electric power systems are crucial measures to achieve the climate targets proposed in the Paris Agreement for countries around the globe. To this end, optimization tools have been adopted for the planning of reliable, environmentally responsible, and cost-effective energy transition, under various types of constraints regarding capacity requirements, climate targets, energy systems operations, and availability of variable renewable energy. Optimization solutions have provided valuable insight into energy transition planning for the European Union [105], the United States [106], China [107], and many other countries or regions around the world. To address the potential uncertainties that may exist in future smart energy systems, robust optimization [39] and stochastic programming [108] approaches have been developed to provide insights for systems design and operations [109]. As energy transition optimization that aims to address systems design and operations simultaneously tends to be computationally expensive, researchers have integrated machine learning with optimization to alleviate the computational demands while maintaining the reliability of future energy systems design [110].

Besides the applications on energy transition planning, optimization has also been extensively used in the operations of smart energy systems with various functionalities, such as enhancing energy flexibility, improving energy systems reliability, reducing systems operations cost, and increasing resilience to extreme conditions, among others. For flexibility, optimizing the integration of multiple energy networks, which include the electrical grid, the district heating network, and the gas network, can enhance the flexibility of future smart energy systems with an increasing penetration level of renewable energy [4]. As for reliability, optimization tools are capable of capturing the energy systems uncertainties, such as fluctuations of wind power outputs that are significantly affected by weather conditions, and operations can be addressed by incorporating the uncertainty information and systems reliability requirements in the modeling constraints [111]. Economically, the operations cost of smart energy systems can be minimized through optimization based on mathematical programming, while ensuring that the systems' operational restrictions are not violated using mathematical programming models [112]. In terms of resilience, as climate change and extreme events can considerably affect both the demand and supply sides of future energy systems, incorporating such factors through optimization tools would effectively facilitate the energy systems design against extreme conditions [113].

3.2. Time series and sequence-to-sequence learning

Time series prediction is to give the change of a certain quantity in a period in history to predict the change in a future period or a moment in the future. According to the given historical data variables, it can be further divided: one only provides the historical data that needs to be predicted, which can also be called autoregressive prediction; the other provides other variables at the same time, such as predicting the temperature in the next few days. Time series problems are not limited to predicting the future, and there exist other common research directions, including time series classification that outputs the belonging category of a given period signal, and time series anomaly detection, among others. For smart energy systems, time series facilitate the design and operations of the energy sector. Meschede et al. [114] took La Gomera in the Canary Islands as an example in 2019, using EnergyPLAN to simulate different probability input time series, and determined 100% renewable energy with variable probability input data and the robustness of the latest design process of the storage system, the combination of vehicle-grid and electric-hydrogen shows the best economic performance. Zhang et al. [115] established a general probabilistic time series data model to solve the problem of the lack of fine-grained time series datasets in distribution-level smart grids, using generative adversarial networks to synthesize datasets. Statistical tests are performed as well as classical machine learning tasks, and empirical results show that synthetic and real datasets are indistinguishable.

For time series forecasting, it is usually necessary to output the forecast values of multiple time points in the future, which is a **multi-output problem**. Times series can be used for forecasting applications in the operations of smart energy systems. Rahman et al. [116] implemented LSTM in predicting electricity consumption for commercial and residential buildings in medium-to-long terms, which generally leads to lower relative error when compared with conventional multi-layered perceptron neural networks. Lv and Wang [5] demonstrated the effectiveness of incorporating sequence-to-sequence learning in complex wind speed forecasting applications. Rizwan et al. [117] studied the disturbance of the protection coordination caused by the change of the fault current level resulted from the wind speed change in the integrated power system of the wind farm, and they proposed a robust adaptive overcurrent relay coordination scheme. The wind speed is predicted by inputting historical time series data through the ANFIS-SARIMA hybrid algorithm [117], and the fault current level is calculated in advance. The optimal relay coordination is achieved by optimizing the relay settings according to the predicted fault current level. Markvart et al. [118] proposed a hierarchical process based on the observed time series of solar radiation. Qureshi et al. [119] proposed a fast and scalable quasi-static time series simulation algorithm based on a linear sensitivity model for estimation with various discrete step control elements. An advantage is that the model relies on linear sensitivity, and the computation time is significantly reduced compared to traditional quasi-static time series simulation algorithms.

3.3. Federated learning

The giant companies in the tech industry monopolize a large amount of data and information, and it is often difficult for small companies and researchers to obtain such data, which leads to the continuous widening of the levels and gaps between enterprises. Realizing the exchange and integration of data and information is difficult, and joint modeling needs to overcome many barriers. In response to the above pain points, federated learning gives the answer. **Federated learning** is a concept pioneered by Google Research in 2016 [120]. This technology enables joint modeling without data sharing. Specifically, the own data of each data owner (individual/enterprise/institution) will not leave the local area. Through the parameter exchange method under the encryption mechanism in the federal system, a global shared model is jointly established, and the built model only serves the local target in the respective region. Although there are some similarities between federated learning and distributed machine learning, federated learning has its own characteristics in terms of application fields, system design, and optimization algorithms. When the amount of data is huge and the computing resource requirements are high, distributed machine learning has obvious advantages, as it stores independently identically distributed (IID) data or model parameters on each distributed node. The central server mobilizes data and computing resources to jointly train the model. Due to differences in the distribution of clients, such as geography and time, federated learning often deals with non-independent and identically distributed (non-IID) data. Combined with the current situation of federated learning, this subsection stratifies the federated learning system and organizes the relevant achievements of federated learning according to modules, as well as their applications in renewable transition planning and smart energy systems operations.

To improve computing efficiency and reduce energy consumption, federated learning allows training models with a certain degree of performance bias but provides data security and privacy protection for all parties involved. There are two commonly used frameworks for federated learning, one is a **client-server architecture**, and the other is a **peer-to-peer network architecture**. Moayyed et al. [121] proposed a hybrid method of network resilience based on federated learning and convolutional neural network (CNN) procedures for short-term wind power forecasting, which is a simple example for the application of energy systems. At the physical level, a federated learning system generally consists of a data holder and a central server. The work of the federated learning center server is similar to that of a distributed machine learning server, which collects the gradients of each data holder and returns new gradients after performing aggregation operations in the server. In a cooperative modeling process of federated learning, the training of local data by the data holder only occurs locally to protect data privacy. Based on these features of federated learning, Venkataramanan et al. [6] proposed a distributed algorithm that transmits models of energy consumption and electricity generation patterns without revealing consumer data to solve the problem of distribution at the consumer level, which fully protects the privacy of user consumption and improves accuracy.

Federated learning processes generally consist of four steps, including system initialization, local calculation, center aggregation, and model update. As for the difference between federated learning and traditional distributed learning, both methods based on the client-server architecture are used to process distributed data, but they differ in terms of application fields, data attributes, and system composition. Furthermore, federated learning has five features, including supporting non-IID data, fast convergence, security, privacy, and supporting complex users. By taking advantage of these features, federated learning has demonstrated its effectiveness in a wide range of smart energy systems operations applications. Specifically, federated learning has been investigated for flexibility forecasting that builds privacy-preserving energy portfolios with aggregated demand data [122], learning power consumption patterns collaboratively without revealing individual power traces [123], load prediction that trains a single model using all participating smart meters without sharing local data [124], diagnosing fault types with enhanced model generalization [125], and short-term solar power forecasting [126].

3.4. Computer vision for smart energy systems

Computer vision is one of the most mature artificial intelligence technologies with highly disruptive implications for energy industries. Computer vision utilizes advanced computing and image recognition technologies. Images acquired from cameras are analyzed using image processing and machine learning methods, such as deep neural networks. Modern architectures combine AI vision and edge computing with the Internet of Things (IoT) [127], switching AI computing from the cloud to the edge of the network [128]. The implementation of connected edge devices for on-device machine learning makes it possible to implement powerful large-scale AI vision systems. Unlike most sensor technologies, an image recognition system is easy to implement because it has a small footprint and minimal impact on existing infrastructure; security cameras can be reused. As a result, such AI vision systems are also easy to maintain. AI vision systems are very cost-effective and can effectively cover large areas, even in remote and distributed areas. This makes computer vision technology suitable for large-scale solutions in the smart energy systems.

Computer vision technology is used today in a wide range of energy applications, including AI vision inspection and monitoring, energy infrastructure detection, anomaly detection, and intelligent control of field personnel and operational behavior, among others. One of the popular research directions that are directly related to urban renewable distributed energy systems is rooftop photovoltaic (PV) panel identification based on remote sensing images. Obtaining the location information of the existing PV panels through remote sensing technology (*e.g.*, aerial and satellite photography) has been emerging as a widely discussed topic [129]. For advancing practical, scalable, and cost-effective data collection, segmenting solar panels from remote sensing images, also called solar/PV panel segmentation, has been drawing increasing attention since the late 2010s. The early work of PV panel detection or segmentation relied more on manual feature design: the researchers extracted features describing the color, edge, shape, and texture of image pixels and applied statistical methods to identify PV panels [130]; the application of machine learning methods like random forest and support vector machine was proven to improve the identification accuracy [131]. Besides, hyperspectral remote sensing images would better indicate the unique spectral characteristics of PV panels from other objects [132,133], which can help to construct more distinguishing features. However, manual-designed features have been confronted with big challenges in effectively representing the variety of the material property, the outdoor environment, and the imaging condition, which largely restricts the accuracy and generalization capability of these methods.

Deep learning techniques, such as CNN, which allow for automatic feature learning and extraction from the data, are now becoming more popular for PV panel segmentation. One of the earliest attempts to apply deep learning to PV panel segmentation was deploying the VGGNet for PV panel detection [134], but the results can only indicate whether the image contains PV panels or not. Subsequently, by applying fully convolution networks following different fashions, pixel-wise segmentation was achieved by many deep-learning-based PV panel segmentation models [135,136]. Typically, DeepSolar, which incorporated classification and segmentation in a single CNN, has constructed a solar installation database for the contiguous U.S. [7]. By far, although the deep-learning-based methods have proven more effective than earlier methods in obtaining relatively reliable segmentation results, great challenges still remain in further improving the accuracy and robustness [137], such as the significant variance of panel size, uneven sample distribution, homogenous texture, and heterogeneous color.

Computer vision has demonstrated its applicability in the energy industry to facilitate systems operations. Phil-vision GmbH and Stemmer Imaging provide machine vision systems to protect endangered birds from the wind turbine blades while maintaining smooth operations of the wind farms [138]. Based on deep learning methods with 500, 000 training images, the computer vision system recognizes large birds of prey and tracks their flight paths, and the system aims to shut down wind turbines only when protected birds move within a certain distance of the turbines, in order to protect endangered birds and avoid long, expensive shut-down times of the wind turbine. Computer vision has also been implemented in the oil and gas industry, with applications on maintenance, service life prediction, safety monitoring, reducing business interruption, non-destructive inspection, and systems corrosion analysis [139]. From the demand side of energy systems, leading industrial cooperations, such as ABB [140], Siemens [141], and GE [142], have applied AI-based computer vision to improve the energy efficiency of their operations and services to their clients.

3.5. Explainable and trustworthy AI

The core idea of **interpretable machine learning (IML)** is that when choosing a model, it is necessary to consider both the prediction accuracy and interpretability of the model and try to find the best balance between the two, contrary to traditional black-box models that only consider prediction accuracy. For models with a single indicator, such as low mean squared error, explainable AI not only gives the predicted value of the model but also the reason for obtaining the predicted value, thereby realizing the characteristics of security, transparency, and fairness of the model. In addition to the single performance evaluation, the evaluation of the model should also add a dimension to express the "expressiveness" of the model, and interpretability is one of them. For a model, interpretability refers to the ability of the model to be expressed in plain and easy-to-understand language, and it is an ability that can be understood by humans. Interpretability is usually subjective, and the degree of interpretation varies for different people, so it is difficult to measure with a unified indicator. If the interpretation of the model conforms to our cognition and way of thinking and can clearly express the prediction process of the model from input to output, then we will consider the interpretability of the model to be good. Local explanation refers to explaining how the predicted results of a sample or group of samples change when the input value changes. Global interpretation refers to the interpretation of the entire model from input to output. From the global interpretation, one can obtain general laws or statistical inferences to understand the impact of each feature on the model. Kruse et al. [143] proposed an interpretable AI model based on modern machine learning methods to quantify and explain fundamental aspects of power system operation and stability. Pütz et al. [144] revealed an important correlation between non-embedded high-voltage direct current (HVDC) operation and grid frequency stability using explainable AI.

Explainability is also a key component for developing trustworthy AI which is lawful, privacy-protecting, and technically robust. The aim of trustworthy AI is to resolve the "black box" issue, lack of transparency, and concerns about data security associated with conventional AI models [145]. Integrating trustworthy AI with future smart energy systems can effectively facilitate operations, as it involves transparency, privacy, autonomy, and legitimacy to address the systems complexity and uncertainty resulted from decentralization and high penetration of renewable energy [146]. In terms of the future direction of explainable and trustworthy AI, explainable machine learning provides a new perspective for model evaluation metrics [147]. Model designers should consider both accuracy and interpretability when designing or optimizing models. To improve the interpretability of the model for renewable transition and smart energy systems, we can take the following two approaches. One is to reduce the complexity of the model structure, such as reducing the depth of the tree model at the expense of model accuracy in exchange for interpretability [148]. The other is using post-assistance attribution analysis methods and visualization tools to obtain the interpretability of the model after training, which aims to maintain the original accuracy of the model [8].

4. Use cases and demonstration examples

The extensive research studies on integrating emerging computing, information, and communication technologies with energy transition and smart energy systems have incited the development of use cases in the industry. AI-based technologies demonstrate exceptional performances in design, analysis, prediction, and operations in smart energy systems. Quantum computing shows unique advantages in dealing with complex problems in smart energy systems that are extremely computationally expensive to solve for classical computing systems. Blockchain provides economic opportunities through integrating crypto-assets with energy systems, as well as innovative mechanisms for energy trading. 5 G/6 G will improve the connectivity and responsiveness of smart energy systems, which can facilitate operations and decarbonization of the systems.

AI-based technologies can benefit energy transition planning and the management of smart energy systems in an effective and efficient manner, particularly in cases dealing with massive amounts of data. For instance, in order to maximize the utilization of wind energy, Vestas runs AI-based simulations and control using Microsoft Azure high-performance computing and reinforcement learning-based controller design platform DeepSim to tackle the shadow effects caused by the wake of wind turbines and to recapture energy with wake steering [149]. Uncertainty and prediction are crucial for the smooth operation of the energy systems, and Argonne National Laboratory effectively informs more reliable grid planning and operations with higher computational efficiency compared to conventional approaches using both supervised and unsupervised learning approaches [11]. Traditionally, energy systems planning problems are addressed using difficult mathematical programming models that can take hours or days to solve, and the advantage of AI-based approaches is avoiding the time-consuming computational process right before making the decisions. Instead, AI models are trained with big data ahead of time, and the decisions can be obtained right away after adjusting the modeling input. Besides the advantages of incorporating AI in smart energy systems, it is worth noting that such integration comes with challenges that need to be addressed before large-scale application, such as the impacts of AI on entrenched procedures, regulatory frameworks, and systems reliability [150].

The emerging quantum computing, blockchain, and 5 G/6 G technologies also demonstrate applicability in smart energy systems through physical-world use cases. For quantum computing, IBM partnered with a German utility company to explore quantum solutions for the rapidly decentralizing energy workflow using quantum-based approaches to solve large-scale complicated energy procurement, trading, and hedging optimization problems that are difficult for classical computing systems [151]. As for blockchain, it facilitates the development of innovative mechanisms that mainly address the trading between utility companies, prosumers, and consumers in decentralized smart energy systems, as demonstrated through microgrid applications in Brooklyn [12] and in Australia [152]. Furthermore, applications in Texas remarks that crypto-assets based on blockchain technology can offer economic opportunities to benefit from the efficient utilization of renewable energy [153]. In terms of communication, 5 G has been adopted in smart energy systems in China, providing multiple types of services, including intelligent peak shaving, smart voltage boosting, and effective energy storage [154]. 5 G will also lead to an immediate and catalyzing impact on reducing CO2e emissions in Europe, as pointed out by Ericsson [155].

5. Outlook

The emerging information and communication technologies have demonstrated a wide range of applications that facilitates the designing and scheduling of smart energy systems, while knowledge gaps still exist in terms of further integration of the technologies and the energy sector. For instance, it would be worth investigating to improve the sustainability of incorporating cryptocurrency with future deep decarbonized smart energy systems while achieving high penetration levels of renewable energy and maintaining sustainable systems operations, given the rising concerns on the waste of renewable energy and the climate impacts of digital asset trading associated with the blockchain technology. Studies have been conducted to explore new schemes to mine cryptocurrencies in an environmentally sustainable manner that can significantly alleviate the operations burden of energy systems [156]. For example, with the growing share of wind energy in the electric power systems, the additional wind farms that have just been constructed may choose to anticipate production and use the electricity as input to mine bitcoins [157]. Using this scheme, the revenues from bitcoin mining can help compensate the anticipation costs of the wind farms and serve as a hedge option that allows the wind energy companies to generate earlier and less risky cash flows against the sale in the spot market with volatile prices. Therefore, associating bitcoin mining with the construction of renewable power generation facilities incentivizes early investment and the transition toward carbon-neutral smart energy systems. Furthermore, cryptocurrency miners are capable of providing valuable grid-level services in the electric power market [158]. Specifically, cryptocurrency miners can be deployed to absorb the fluctuating uncertainties of energy supply and provide flexibility to the demand side, based on optimal system coordination. The miners can receive revenue from providing grid services and cryptocurrency rewards, and the electric power systems can benefit from the reduced electricity prices. Therefore, the active participation of cryptocurrency miners in demand response programs could be a win-win strategy for both the cryptocurrency mining companies and the system operators in future smart energy systems.

Research opportunities emerge with the growing integration of cryptocurrency mining and future energy systems with high penetration of renewable energy. For instance, it is crucial for sustainably incorporating cryptocurrency mining in smart energy systems to investigate the values of this integration, in terms of economic revenue from crypto mining, ancillary services for the power grid, and utilization of wasted renewable or fossil energy, which can be demonstrated by involving crypto mining in the national or state-level smart energy systems for the next decade. Two research challenges exist to address the sustainability of cryptocurrency in smart energy systems. The first challenge is to benchmark the impacts and performance of cryptocurrency mining in smart energy systems with conventional energy storage systems, from the perspectives of economic benefits, systems reliability, reduction of energy waste, and environmental impacts. The other challenge is to explore the synergy of incorporating bitcoin mining and energy storage options for future energy systems, through studying the energy and climate impacts of different crypto mining capacities and different levels of renewable energy penetration. Studies on this topic can provide insights for improving the economic performance and grid reliability of future smart energy systems resulted from cryptocurrency mining rewards and electricity demand flexibility of mining activities on a time scale of a decade. It also demonstrates the advantages and disadvantages of cryptocurrency mining in smart energy systems demonstrated in comparison to the valuation of conventional energy management approaches, which takes account of various ancillary services. Additional research work can also be conducted to reveal the impacts of cryptocurrency mining involvement in smart energy systems through country-level or state-level applications, in terms of accelerating the renewable energy transition, facilitating fast demand response, reducing fossil energy waste, and effective utilization of renewable energy curtailment and off-the-grid new wind or solar farms.

6. Conclusion

Decarbonizing energy systems is crucial for climate change mitigation, as the energy sector is the dominant contributor to global greenhouse gas emissions. To address the two major challenges of energy systems decarbonization in terms of renewable transition planning and sustainable systems operations, emerging information and communication technologies are increasingly incorporated in the energy sector to facilitate both the design and operations of future smart energy systems with high penetrations of renewable energy and decentralized structures. This work reviewed the recent academic findings and industrial applications of emerging information and communication technologies in smart energy systems and renewable transition of the sector, and the technologies reviewed in this study could be categorized into artificial intelligence (AI) and non-AI technologies. The AI-related technologies in smart energy systems included optimization, time series, sequence-to-sequence learning, federated learning, computer vision, explainable AI, and trustworthy AI.

Non-AI information and communication technologies also facilitated renewable energy transition and systems operations, such as quantum computing, blockchain, next-generation communication technologies, and the metaverse. In terms of non-AI technologies, quantum computing presented unique advantages in smart energy systems in terms of solving complex problems, which were extremely computationally expensive for classical computing systems. Blockchain could be the basis for developing innovative mechanisms for energy trading and gaining economic benefits by incorporating crypto-assets with future smart energy systems. Next-generation communication technologies would improve connectivity and responsiveness, which could lead to more efficient and smarter operations of the energy systems with high penetration of renewable energy and increased distributed energy sources. The booming metaverse sector could have significant impacts on the design and operations of smart energy systems in the coming decades, owing to the potential widespread adoption and its profound changes to various socioeconomic activities.

AI-related technologies demonstrated effectiveness in smart energy systems through a wide range of academic research and industrial applications. For instance, optimization could minimize the economic cost of energy systems operations and renewable transition planning. Time series and sequence-to-sequence learning emerged as promising tools to be embedded in smart sensors, which could result in scalable solutions to analyze energy consumption and provide reliable forecasts for smart energy systems. Federated learning was applied for multiple applications in energy systems operations, including building privacy-preserving energy portfolios with aggregated demand data and learning power consumption patterns collaboratively without revealing individual power traces. Computer vision was also extensively applied in smart energy systems, such as providing location information for renewable generation and protecting wind turbine blades while maintaining smooth operations of wind farms. Explainable and trustworthy AI based on modern machine learning methods could help quantify and explain fundamental aspects of power system operation and stability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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