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Advancements in Communication and Information Technologies for Smart Energy Systems and Renewable Energy Transition: A Review

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Abstract
As the energy sector significantly impacts global greenhouse gas emissions, it is essential to decarbonize energy systems to mitigate climate change. Two primary obstacles in decarbonising energy systems include planning for renewable transitions and ensuring sustainable system operations. However, there is hope on the horizon. The potential of new information and communication technologies to enhance future innovative energy systems' planning and operational phases is immense. These systems are characterized by high renewable energy integration and decentralized configurations. This paper offers an extensive examination of how these emerging technologies, such as artificial intelligence, quantum computing, blockchain, advanced communication technologies, and the metaverse, apply to renewable transition and intelligent energy systems. It discusses pertinent research avenues by analyzing existing studies. The review includes industrial use cases and practical demonstrations of innovative energy technologies, providing a glimpse into the promising future of energy systems.

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1. Introduction
Shifting from traditional, carbon-heavy energy systems to intelligent and renewable energy (RE) infrastructures is vital to decarbonising global efforts and combating global warming, given that greenhouse gas emissions worldwide are caused mainly by the energy sector (International Energy Agency (IEA) 2022; Barrales-Ruiz and Neudörfer 2024). Two principal challenges in realising decarbonised energy systems include planning the energy transition and managing sustainable system operations (O'Dwyer et al. 2019; Chang et al. 2021; Lonergan et al. 2023; Pavlović et al. 2023). Designing energy transitions focuses on planning changes in power transmission, energy storage, and generation capacities, with these scheduling judgments typically occurring over extended yearly intervals. In operations, ensuring reliability

and flexibility is essential for intelligent energy systems (SES) that integrate the electricity, heating, and transportation sectors. These systems manage demand and supply changes and uncertainties across several time scales, such as intra-hour, daily, hour-by-hour, and seasonal periods. To support the decarbonization of energy systems, employing emerging technologies would significantly enhance the preparation of energy transitions and intelligent systems of energy controls. **Fig. 1** shows the educational and industry promise of several technologies, including AI, quantum computing, blockchain technology, advanced communications technology, and the other worlds.

Academic research has extensively explored the integration of new technologies into the energy transition and SES. AI-based tools such as optimisation, sequence-to-sequence learning, federated learning, computer vision, and explainable AI have proven effective in tackling complex issues in intelligent computerised power plants that are both precise and efficient (Zhang et al. 2018b; Lv and Wang 2022; Wang et al. 2022; Komerska et al. 2023; Kumar et al. 2024; Pang and Dong 2024). Quantum calculating has demonstrated exceptional computational capabilities for tasks that are infeasible with traditional devices, offering a novel solution for addressing the intricate design and operational challenges in decarbonised innovative energy sources of the future (Olatunji et al. 2021; Ajagekar and You 2022a; Liu et al. 2022c). This technology also aids in achieving national decarbonisation objectives, as shown in **Fig. 2**. Distributed energy production is expected to be a key component of SES, necessitating advanced mechanisms to monitor trading actions between energy users and providers. With blockchain-based technology, these complicated deals can be tracked in a way that is both autonomous and democratic despite requiring a governing body. Improvements in wireless transmission, including cutting-edge fifth-generation and forthcoming sixth-generation wireless networks, enable effective coordination of operations within SES. These advancements assist in managing the growing complexity of energy systems that arise from the increased integration of RE.

Future energy system planning and operations are anticipated to be profoundly affected by the expansion of the metaverse sector in the following decades due to its potential to displace a broad spectrum of real-world activities that consume energy. Numerous academic research studies have examined the integration of emerging computing, information, and communication technologies into renewable transition and intelligent energy system operations, leading to industrial demonstrations and use cases (Zhao and You 2020; Lee et al. 2024; Phu et al. 2024). AI has proven helpful in intelligent energy system design and operation, where several intricate problems have been successfully addressed (Nasiri et al. 2022; Saadaoui and Omri 2023; Zhao et al. 2023). Also, blockchain technology has demonstrated its usefulness by securely documenting transactions across different microgrids (Mengelkamp et al. 2018; Zhou 2024). The research team behind this project set out to look at how energy efficiency and the shift to RE have used modern technological innovations, both in the classroom and the workplace. It seeks to understand how these technologies are shaping the future of energy infrastructure. This paper offers insights into three critical questions to accomplish this objective: “What are the latest research studies that integrate emerging information and communication technologies within energy transition and SES?”. “How do the various emerging technologies effectively aid in planning renewable transitions and managing system operations?”. “What industrial demonstrations and use cases illustrate the adoption of computing, information, and communication technologies in the decarbonisation and operations of energy systems?”.

What follows is the outline for the remainder of the article. Part two delves into how the multiverse, 5G/6G, the blockchain, and quantum technology can be integrated into the planning and managing of future energy systems. The function of artificial intelligence (AI) based technology in the electricity sector climate change is addressed in Part 3. The topics covered are optimisation, federated learning, computer vision, explainable AI, and sequence-to-sequence and sequential teaching. The perspective and the conclusions are discussed separately in greater depth in Parts 5 and 6.

2. Emerging non-AI ICTs for SES and the RE transition

a. Computation in quantum

Quantum computing has shown exceptional computational capabilities for tasks that supercomputers find intractable. This advantage holds significant potential for enhancing the purpose and controls of future SES (Ajagekar and You 2022a). The benefits of quantum computing stem primarily from its capacity to utilise quantum mechanical phenomena, resulting in computational operations that differ significantly from those of classical computers (Zhang et al. 2023b; Benenti and Casati 2024). Classical computing stores data in bits that have discrete values between 0 and 1. In contrast, quantum computing operates with quantum bits (qubits) that exist in superposition, simultaneously representing the 1 and 0 states. To leverage quantum computing to solve real-world problems, quantum algorithms must be implemented through a quantum circuit interacting with a set of qubits (Ajagekar and You 2022b; Andersson et al. 2022; Gani et al. 2022). Quantum computing has found applications in various engineering fields related to sustainable development. These include optimising energy systems, selecting biomass mixes, and planning sustainable production (Ajagekar and You 2019; Ajagekar et al. 2020; Kaveh et al. 2021; Andersson et al. 2022; Shunza et al. 2023).
Additionally, researchers have applied quantum computing across various innovative energy system applications. Operations related to the power grid, stored energy management, electric governance, and forecasting load are all part of this (Lau et al. 2009; Ho et al. 2018; Xiong et al. 2018; Paudel et al. 2022; K S et al. 2024). Considering AI's extensive use in the RE category, integrating quantum computers using AI could significantly improve energy system planning and execution. Two subfields of quantum artificial intelligence, quantum artificial intelligence and quantum-enhanced optimising are primarily involved in SES applications. The following sections will delve deeper into these subjects.

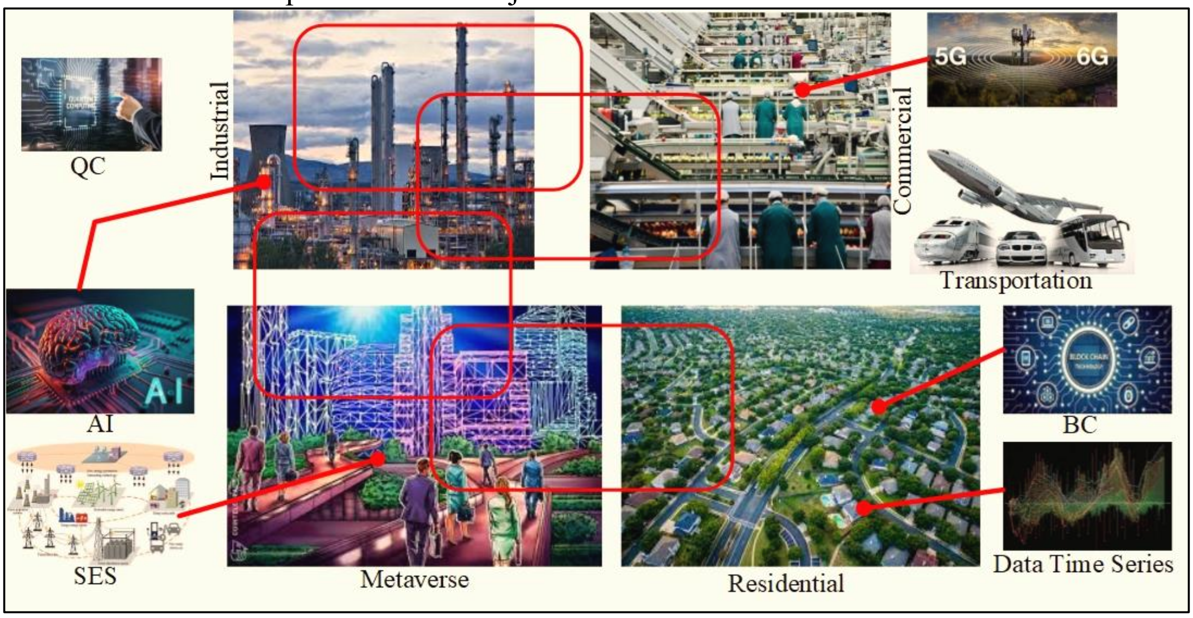

Fig. 1. Technologies of renewable energy transition and intelligent energy systems include BC, AI, 5G, 6G, and Metaverse.

b. *Optimization with quantum enhancement*

Quantum-enhanced optimisation has the potential to offer superior computational efficiency over traditional optimisation methods used on classical computers. Optimisation challenges are prevalent across different aspects of energy system design and operations (Aruta et al. 2023; Choi et al. 2024; Wang et al. 2024b). It is essential to recognise that optimising deeply decarbonised SES often involves NP-hard problems (Khan and Rehman 2013). This indicates that when employing traditional machines for applications on a large scale, the cost of computation increases dramatically. Using algorithms designed for quantum machines can assist with this problem. There is evidence that these techniques outperform the most efficient classical methods regarding computing power. One thing to remember is that quantum optimisation techniques only shine when used for certain kinds of problems with optimisation. However, these advantages are not broad enough to address all varieties of mathematical programming challenges (Liu et al. 2022a; Guo et al. 2023a). The development and management of SES may benefit from computational speedups brought about by quantum-enhanced optimisation. Among these are enhancements to the distribution of electric power, the design of energy infrastructure, and the networks that deliver RE. Continued optimisation and binary optimisation are the two main categories of optimisation methods for SES that use quantum improvement.

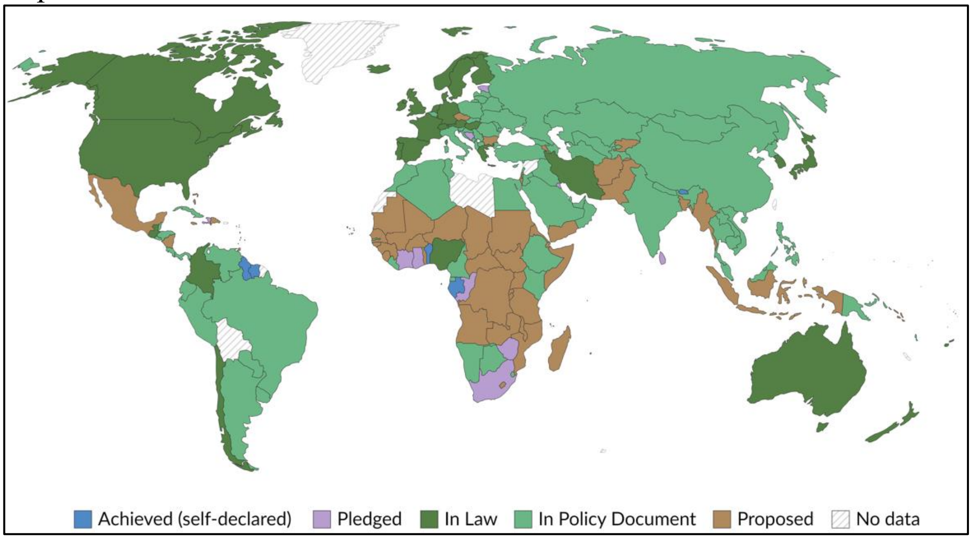

Fig. 2. Decarbonization objectives vary among countries or regions, spesifik the desired year for attaining net-zero greenhouse gases and the commitments made towards climate change.

When dealing with binary optimization problems, choosing variables from sets like {-1, 1} or {0, 1} is necessary. The ability of quantum machines to solve quadratic unbounded binary optimal (QUBO) problems—a type of binary uncontrolled optimal problem—with quadratic goals is already proven (Zhou et al. 2020; Acampora et al. 2023; Blekos et al. 2024). When applied to a wide range of constrained and unconstrained issues, QUBO methods are quite versatile (Lucas 2014). Thanks to its adaptability, SES can use a quantum-enhanced optimising strategy to solve mathematics programming problems. In the field of continuous optimisation, the utilisation of the quantum interior point approach results in significant polynomial speedups. When it comes to tackling issues involving general quadratic programming (QP), linear programming (LP), and semidefinite programming (SDP), this strategy has been shown to be effective (Kerenidis and Prakash 2020). Combining the KKT conditions with multipliers from Lagrange and the Harrow-Hassidim-Lloyd (HHL) quantum method is achievable (Harrow et al. 2009; Jin et al. 2023; Schalkers and Möller 2024). Thus, quantum-enhanced optimisation can improve computing efficiency, which helps prepare and manage SES (QP, LP, and SDP formulations). Electricity transport, charging for electric cars planning, and response to demand network management are all part of this category of activities (Zheng et al. 2018; Lu et al. 2023; Wang et al. 2024a; Yan et al. 2024).

c. Learning using quantum computing

Quantum artificial intelligence can overcome numerous shortcomings of present machine learning methodologies obtained on classical devices, providing potential benefits for intelligent energy networks. There has been a significant amount of application of machine learning to the design, modelling, and operation of smart energy networks (Ibrahim et al. 2020; Yin et al. 2020; Ahmad et al. 2022). Nevertheless, there may be drawbacks for large-scale applications that utilise the physical world, particularly regarding scalability and the complexity of the computations involved (Zhang and Sejdić 2019; Qi et al. 2024; Ram et al. 2024). To overcome these drawbacks, using quantum computers in machine learning activities can be advantageous in enhancing computing efficiency. This, in return, helps make the shift to RE and SES more feasible by applying artificial intelligence methods. Supervised, uncontrolled, and reinforced learning are just a few artificial intelligence activities that can benefit from quantum learning techniques. This indicates that integrating quantum computing into machine learning-based approaches within SES holds promise for enhancing their capabilities (Jadhav et al. 2023; Pandey et al. 2023; Wei et al. 2023). Using quantum technology to improve computational efficiency, quantum artificial intelligence can accomplish acceleration performance across various components of machine learning algorithms. Some of the improvements include making it easier to sample systems that aren't accessible using classical approaches, increasing the accuracy of classifications, and optimising the use of matrices on vectors in multidimensional space vectors (Wei et al. 2023). Harnessing quantum machine learning is essential for identifying tasks that can capitalise on computational advantages when executed on quantum computers. Hence, quantum computing holds promise for mitigating the computational complexities arising from the application of approaches for artificial intelligence in SES, including RL, SU, and other ML frameworks. As an illustration, supervised learning has been helpful in several areas, including electricity price forecasting, energy demand prediction, and electricity storage control (Luo and Weng 2019; Zhou and Zheng 2020; Hosamo et al. 2022; Zhou 2022). Among the many tasks that have discovered a home for autonomous learning are the demand for energy representation, evaluation of periodic electrical data, and RE scheduling with uncertainties (Teichgraeber and Brandt 2019; Zhao and You 2021a; Mancò et al. 2024). Regarding learning by repetition, scientists have used these methods to develop and manage energy infrastructure (Perera et al. 2020; Zhou et al. 2023; Xiong et al. 2024).

d. Energy efficiency with blockchain-based systems

Future SES are predicted to be more sophisticated and decentralised due to the rising integration of variable RE sources and the rise in energy users. Blockchain-based technology could benefit the administration of such energy sources' operations. (Andoni et al. 2019; Rejeb et al. 2024; Ressi et al. 2024). Distributed ledger technology (DLT), which includes blockchains, aims to facilitate decentralised transactions by doing away with centralised administration. A blockchain is a distributed ledger encrypted and continually updated with new data called blocks. Whenever new blocks are added to a blockchain, they contain cryptographic hashes of the blocks that came before them, transactional data, and a timestamp, proving that the data was there when the blocks were created. A chain of linked records is formed by this crypto hash, which effectively connects each block to the one before it. Distributing the ledger across a collection of nodes allows a blockchain to be decentralised. The blockchain is replicated on every computer or node. This redundancy makes sure that over half of the network needs to be controlled to edit or delete data about transactions within the digital ledger. (Sikorski et al. 2017; Guo and Yu 2022). Among the many uses of blockchain technology in SES is facilitating P2P energy trade and energy management inside intelligent grids. From a sustainability perspective, however, examining blockchain technology's substantial energy implications is also essential. Without a governing body, blockchain technology provides a decentralized, democratic, and autonomous means of overseeing energy infrastructure operations. The decentralised nature of SES presents some difficulties, which this capacity helps to alleviate. (Yang et al. 2021; Mathew et al. 2022; Ruan et al. 2024). Energy producers, distributors, dealers, consumers, and prosumers have all benefited from the new systems and systems made possible by blockchain computing. (Di Silvestre et al. 2020). Traders, providers, and providers all participate in global energy trading. Blockchain-based solutions, like PONTON's Enerchain architecture in Europe, have shown encouraging outcomes in real-world testing and execution (Buth et al. 2019; Roth et al. 2022; Al-Sorour et al. 2023).

Managing the collaboration of different parties without a single governing body is crucial to ensuring the smooth operation of SES. Smart contracts like the Stackelberg game, the consortium-blockchain consensus method, and the mathematical programming–based Proof of Solutions method are some models developed to address this difficulty (Chen et al. 2022; Hua et al. 2022; Choobineh et al. 2023). Using digital currencies in energy trade has several benefits for microgrids and energy retailers, including improved demand side management, the integration of prosumers via peer-to-peer exchange, and the facilitation of microgrid operation (Esmat et al. 2021; Mehdinejad et al. 2022; Wu et al. 2022; Alam et al. 2024). Academics and businesses alike are curious to see how blockchain impacts energy infrastructures. One notable example of a blockchain application is Bitcoin, which has recently used more power than every nation combined (de Vries and Stoll 2021). In addition, studies show that to create the same amount of value in the stock market, bitcoin mining typically uses additional power than mining most minerals (apart from aluminium) (Krause and Tolaymat 2018; Li et al. 2019). Greenhouse gas emissions have risen due to the increasing energy demand caused by the growing bitcoin and cryptocurrency mining activities. Researchers expected Bitcoin mining to produce over 23 Mt CO_2 in 2018 and 90 Mt CO_2 in 2021 (Stoll et al. 2019; de Vries 2021; de Vries et al. 2022). Mining for cryptocurrencies is becoming increasingly popular, which is bad news for efforts to slow global warming. Some estimates put the heat from bitcoin emissions alone at more than 2 degrees Celsius by mid-century (Mora et al. 2018). A strategy that uses Bitcoin mining to reduce wind and solar curtailments has been developed by Niaz et al. to address the energy and environmental challenges related to Bitcoin. In addition to making money off the reduction of renewable electricity use, this framework seeks to lessen Bitcoin's negative impact on the environment (Niaz et al. 2022a). Integrating carbon capture technology with RE sources is one way to address the environmental challenges of bitcoin mining. This method takes advantage of the fact that RE is carbon neutral, that carbon capture benefits sustainability, and that bitcoin is profitable (Niaz et al. 2022b). Notably, altering the consensus process can also reduce blockchain technology's energy usage and environmental effects. For instance, bitcoin's proof-of-work method is a significant factor in its high-power usage. On the other hand, the second-largest cryptocurrency, Ethereum, switched from proof-of-work to proof-of-stake as its consensus method in 2022. With this change, power usage should drop by 99.95% since the blockchain no longer requires computing operations that need a lot of energy (de Vries 2018; Gallersdörfer et al. 2020; Qin et al. 2023).

e. Smart energy systems can benefit from 5G and 6G.

Over the past several decades, wireless communication technologies have consistently evolved, with 5G and the forthcoming 6G networks enabling more effective management of SES. (Yap et al. 2022). As RE becomes more prevalent and energy demand diversifies, energy systems have grown increasingly complex. To maintain the reliability of these systems, robust communication technologies that support coordination among energy system participants have become crucial (Hui et al. 2020; Boopathy et al. 2024; Ziwei et al. 2024). The market's most recent mobile communication technology, 5G, offers data speeds of up to 20 Gbps and latencies ranging from 1 to 10 milliseconds. The advancements by 5G have positively impacted various applications within SES, including demand response (DR), decentralised algorithms, and the exchange of information for renewable electricity generation. Looking ahead, 6G is anticipated to dramatically increase data speeds, potentially reaching 1 Tbps, lowering latency to under 0.1 milliseconds, enhancing reliability to 9-nines, and extending coverage (Gupta et al. 2021; Park et al. 2022; Kar et al. 2023). These advancements enable 6G to deliver ultra-reliable low latency communications (URLLC) services, supporting the dependable functioning of intelligent grids, secure vehicular networks, remote monitoring of equipment, and high-speed energy trading through blockchain technology (Hui et al. 2020; Boopathy et al. 2024; Ziwei et al. 2024). The latest developments in communication technologies have positively impacted managing SES, with 5G being researched and adopted for several critical roles in energy systems. This includes boosting power system reliability, improving intelligent grid security, and aiding energy management within intelligent buildings. In particular, 5G is well-suited for innovative grid communications, given the need to collect, exchange, and process vast amounts of data to analyse and guide system operations and services (Rawat et al. 2016; Esenogho et al. 2022). Instant access to energy-related data from both the demand and supply sides is essential for managing intricate SES that integrate distributed energy resources (DER) and the Internet of Things (IoT) (Hussain et al. 2019; Safari Fesagandis et al. 2021; Ge et al. 2022).

To resolve information exchange challenges, the high bandwidth, substantial capacity, and low latency characteristics of 5G have shown promise for communication among various competent grid participants, comprising market participants, system administrators, energy suppliers, computer power, and consumers of the grid (Feng et al. 2021; Lalle et al. 2021). With 5G mobile phone technology, electrical networks may be more dependable, efficient, and secure by utilising cloud computing, actual time energy information analytics, and demand planning (Ahmadzadeh et al. 2021; Huseien and Shah 2022). Beyond its grid-level applications, 5G supports energy management in smaller settings such as intelligent buildings. This is possible thanks to the vast amount of high-quality data on energy use and demand forecasts for IoT devices and distributed subsystems shared through 5G wireless networks (Zhou and Li 2020; Alhassan et al. 2024; Kaur et al. 2024). Next-generation 6G wireless networks will offer enhanced services and facilitate the operation of SES. This is due to their attributes of faster data rates, reduced latency, and improved heterogeneous connectivity (Khan et al. 2020; Khalifa et al. 2023). Since 6G is expected to offer quicker communication with enhanced data rates, lower latency, and more excellent reliability compared to 5G, it's anticipated to resolve communication challenges among various bright grid elements. The improved connectivity of 6G also supports numerous operational enhancements for SES, including peer-to-peer energy trading, smart metering for prosumers and consumers, real-time pricing, optimised system operations, AI-assisted forecasting for RE production, and electric vehicle management (Phan et al. 2020; Zhang and Chen 2020; Yi and Smart 2021).

Additionally, 6G wireless networks are expected to offer more scalable and diverse connections than 5G, facilitating the development of space-air-ground integrated networks that aim to create a digitised and interconnected world beyond the capabilities of 5G communication technologies (CHENG et al. 2022; Ray 2022; Sharif et al. 2023). It is anticipated that 6G connections will be quicker and more advanced than current satellite-based networks (Wolfstetter 2022). As a result, many real-world devices are linked via 6G networks, allowing different types of equipment to interact seamlessly. This interconnectedness forms the basis for precise real-time monitoring and operation of SES (Viswanathan and Mogensen 2020; Xu et al. 2020; Guo et al. 2022). The vast number of interconnected devices on 6G networks raises concerns about their energy usage, given that many are wireless and mobile. Energy harvesting could be a viable solution to this challenge (Gustavsson et al. 2021; Velasquez et al. 2022; Banafaa et al. 2023). The 6G wireless system is anticipated to play a crucial role in the rapid growth of the metaverse industry. This development could considerably affect the energy sector and the environment, as explored in the following section (Tang et al. 2022).

f. Metaverse is used to reduce climate change and enhance intelligent energy systems.

An extensive system of linked, three-dimensional digital environments made possible by Web 3.0, blockchain, VR, and AR innovations is known as the metaverse (Jung et al. 2022; Kshetri 2022a; Zhao et al. 2022). The advent of metaverse technology could reach billions of users and influence every industry. The metaverse's market opportunity is estimated to surpass $1 trillion in annual global revenue (Citi 2022; Moy and Gadgil 2022; Klaus and Manthiou 2024). The anticipated swift expansion of the metaverse industry could lead to notable and far-reaching shifts in economic endeavours as the metaverse integrates the real and virtual worlds to allow individuals to do everything from work to play to relax to learning to interact. The growth and development of the metaverse hinge on the enhancement of various critical technologies, including VR, AR, Web 3.0, and non-fungible tokens (NFTs). A fundamental aspect of the metaverse involves placing each user within a virtual 3D environment and connecting them with others via the internet. Compared to traditional mobile devices, virtual reality (VR) and augmented reality (AR) typically offer a more compelling means of immersing oneself in three-dimensional environments (Adachi et al. 2022). The user experience beyond VR/AR applications can also be improved with the help of haptic feedback and other technologies (Yu et al. 2019). Web 3.0, the latest version of the World Wide Web that embraces the concept of decentralisation, can assist in establishing connection rules for the metaverse, allowing for the interchange of information across various users or virtual worlds (Kshetri 2022b). In contrast to the era of Web 2.0, when a small number of centralised technology companies were known as "Big Tech, the decentralised nature of Web 3.0 makes it possible to run virtual worlds built on the metaverse independently (Skripochnik et al. 2020; Adachi et al. 2022).

Businesses operating in the metaverse would do well to follow the lead of decentralized finance (DeFi) and NFT (Zetzsche et al. 2020; Wang et al. 2021; Ali et al. 2023a; Davies et al. 2024), two blockchain-based financial management systems that facilitate peer-to-peer (P2P) transactions devoid of a trusted third party. This would be in line with the trend toward decentralization in Web 3.0. Virtual marketplaces for collectables, artwork, and real estate based on virtual territory can be supported by NFTs since each is unique and can be traded (Fonarov 2022). In the subsequent decades, the design and operations of SES could be significantly influenced by the booming metaverse industry, which could have far-reaching effects on environmental sustainability. More specifically, as more and more people use metaverse-based applications—including virtual learning, working, and travelling—fewer and fewer people use their physical world counterparts, like on-site learning, physical tourism, and on-site employment. Commercial and industrial activities are anticipated to require less energy if they have access to metaverse alternatives. This digitization will lower transportation demand, energy consumption, and emissions, as the metaverse growth can relocate several in-person activities. The flip side is that as the metaverse grows, so does the amount of energy needed by gadgets that rely on it and the amount of time people spend at home, leading to higher energy consumption overall. Hence, further research on the metaverse's overall effects on energy, the environment, and climate change is needed to determine how future SES should be planned and operated to accommodate the metaverse expansion.

3. The application of artificial intelligence to intelligent energy systems and the shift to RE

AI is expected to be a game-changer in energy transition and smart energy system operations because its revolutionary tools tackle complicated energy sector challenges with astonishing precision and high computing efficiency. For instance, optimization-focused deep learning may, with remarkable accuracy, understand the patterns of load changes from past data and produce state-of-the-art performance in load prediction (Jia et al. 2022; Assareh et al. 2023; Armghan et al. 2024). Secure smart energy system operation and effective dynamic attack detection are both made possible by AI-based techniques (Hamedani et al. 2019; Kim et al. 2023). Additionally, smart sensors that incorporate time series and sequence-to-sequence learning show promise as scalable and cost-effective solutions for decomposing small-scale energy usage and producing accurate predictions for SES (Coelho et al. 2016, 2017; Saini et al. 2023). Also included here are some of the most cutting-edge AI-based approaches, AI techniques that have demonstrated potential in SES include federated learning, visual computing, transparent artificial intelligence, and trustworthy AI.

a. Time series and learning from sequences to other sequences.

To forecast the change of a specific number in a future period or instant, time series prediction uses the change of that quantity over a historical period. Two subtypes can be defined according to the variables in the historical data: one that gives the necessary historical data for prediction (also known as autoregressive prediction) and another that offers multiple variables at once (for example, a temperature forecast for the next few days). In addition to future prediction, other popular research areas in time series include, for example, time series anomaly detection and time series classification, which both provide the belonging category of a particular period signal. Time series help with energy sector operations and design for SES. Using the Canary Island of La Gomera as an example, Meschede et al. (2019) used Energy PLAN to model various probability input time series in 2019. They found that, when factoring in the robustness of the most recent storage system design and the use of variable probability input data, a combination of electric hydrogen and vehicle grid power produced the most remarkable financial performance. Zhang et al. (2018a) synthesized datasets utilizing generative adversarial networks and developed a generic model for data collected in time using probability to handle the issue of distribution-level smart grids without fine-grained time series datasets. According to empirical results, natural and synthetic datasets are shown to be statistically and classically machine learning tasks indistinguishable.

The projected values of numerous future time points are typically required for time series forecasting, making it a multi-output problem. For smart energy system operations, time series can be utilized for forecasting purposes. To forecast commercial and residential buildings' electricity usage in the medium to long term, Rahman et al. (2018) used LSTM, which often results in lower relative error than traditional multiple-layer perceptron neural network techniques. Complex prediction of wind speeds systems that used sequence-to-sequence learned were found to be helpful (Lv and Wang 2022). The impact of wind speed changes on the integrated power system of wind farms and how they disrupt protection coordination. They suggested a resilient, adaptive overcurrent relay coordination scheme as a solution. The ANFIS-SARIMA hybrid algorithms anticipate the wind speeds and fault present position by analyzing historical periodic data (Al kez et al. 2020; Rizwan et al. 2020; Erdiwansyah et al. 2021, 2022). The most efficient coordination of relays is accomplished by fine-tuning the relay settings per the anticipated fault current level. The time series of solar radiation was used to propose a hierarchical mechanism (Markvart et al. 2006; Nwokolo et al. 2023). Qureshi et al. (Qureshi et al. 2018) detailed a linear sensitive model for estimating that uses numerous discrete step-controlling components, on top of which is built a scalable quasi-static periodic simulations method that is quick and accurate. By utilizing linear sensitivity and significantly reducing computing time, the model outperforms conventional quasi-static time series simulation methods regarding computation efficiency.

b. Artificial intelligence optimization and energy system applications

Optimizing SES is a strong suit of artificial intelligence, particularly neural networks. Improving the accuracy of deep learning's processing speed is crucial for energy-related solutions due to the massive volume of data that is a technology feature. Therefore, in artificial intelligence, optimizing using a gradient-descending approach seeks to locate the local lowest value of a provided cost function by determining the best possible values for the associated variables (factors). Calculating the cost function's gradient and proceeding in the opposite direction from the gradient are the two steps that comprise the iterative process. Deterministic optimization based on mathematical programming has broad utility for many energy system design and operation issues. Adjusting the number of choice parameters following a set of inequalities constraints can decrease or increase the objective functions. Such optimized techniques often construct theoretical frameworks to zero in on energy-related issues. In the context of computational optimization, some examples of objective functions that are commonly used are cost minimization, profit maximization, and social welfare maximization. The structure's prospective planning and short-term operating decisions can be reflected in the choice parameters utilized in RE effectiveness.

Conversely, the constraints are the requirements that must be met for the optimal values of the decision variables to be considered valid. The implementation of optimization is both applicable and effective in the process of designing energy transition paths. Power grid digitalization and a decrease in carbon networks are essential steps that must be taken for nations all over the world to meet the climate goals that were outlined in the Paris Agreement. Optimization tools have been implemented to plan a transition to energy that is dependable, ecologically sound, and economical to achieve this goal. Numerous limitations, such as capacity needs, climate goals, power system processes, and the accessibility of the parameter RE, must be considered during the planning stages of this shift.

The energy transition plans of several nations and regions have benefited dramatically from optimization solutions, including the EU, the US, China, and many more (Obringer et al. 2019; Zhang et al. 2020; Pan et al. 2021). To tackle the uncertainties that could be present in SES of the future, methods like stochastic programming and resilient optimization have been created to offer guidance on how to design and run these systems (Gebreslassie et al. 2012; You 2013; Díaz-Trujillo et al. 2020). Because optimizing for energy transitions that consider both system design and operations at the same time can be computationally expensive, researchers have begun to combine optimization with machine learning to reduce these demands without sacrificing the reliability of future energy system designs (Zhao and You 2021b; Lam et al. 2022; Kii et al. 2023). Optimization has found widespread application in SES operations, alongside the transition to RE planning, to enhance energy adaptability, cost, dependability, and adaptability to mitigate the effects of harsh weather. To make future SES with more RE more flexible, integrating multiple energy networks, including the power system, district heating networks, and gas networks, should be optimised (Zhang et al. 2018b). In terms of reliability, optimization tools can capture the uncertainties that are associated with energy systems. Such uncertainties include, for instance, the fact that weather substantially impacts the variability of wind power production. Incorporating uncertainty information and needs for system reliability into logical restrictions allows processes to be addressed (Fang et al. 2019; Hou and Jian 2023; Mi et al. 2024). Optimizing SES using mathematical programming can decrease operational costs while keeping them within operational constraints, which is good from an economic perspective (Anilkumar et al. 2017; Kusakana 2019; Timmons et al. 2019). For future energy systems to be resilient, it is important to incorporate elements like climate change and extreme events into optimization techniques. This will help design the systems to withstand extreme conditions, as these factors can significantly impact both the demand and supply sides of the systems (Perera et al. 2021; Javanroodi et al. 2023).

c. Trustworthy and explicable AI

Interpretable machine learning (IML) is based on the principle that, unlike traditional black-box models, which solely consider prediction accuracy, it is crucial to find a balance between the model's interpretability and prediction accuracy when selecting a model. By conveying the model's expected value and the reasoning behind its prediction, explainable AI brings about the qualities of honesty, openness, and equity. Low average square error scenarios, in particular, benefit from this. There should be more than just one performance metric used to assess a model; interpretability is one such metric that allows us to quantify the "expressiveness" of the model. Regarding models, interpretability is the model's capacity to be described in language humans can comprehend. The difficulty in measuring interpretability with a single indicator stems from the fact that it is often subjective and that people's levels of interpretation differ. When the model's interpretation aligns with human cognitive processes and provides a clear explanation of the model's prediction process, from input to output, we consider the model to have good interpretability. When an input value changes, a local explanation can be provided to explain how a sample's or group's anticipated outcomes change as well. All aspects of the model, from inputs to outputs, are considered in the global interpretation. One can get statistical conclusions or general laws from the global interpretation to learn how each characteristic affects the model. With the goal of quantifying and explaining basic features of power system operation and stability, Kruse et al. (2021) presented an interpretable AI model that is based on recent machine learning algorithms. Using explainable AI, Pütz et al. (2022) demonstrated a significant relationship between grid frequency stability and non-embedded high-voltage direct current (HVDC) functioning.

Developing trustworthy AI that is legal, protects privacy, and is technically robust also relies on explainability. Trustworthy AI aims to address the "black box" problem, lack of transparency, and data security worries related to traditional AI models (Jararweh et al. 2020; Liu et al. 2022b; Singh et al. 2023). Integrating trustworthy AI can improve operation efficiency, privacy, autonomy, and legitimacy in future SES. This will help with the system's complexity and uncertainty caused by centralization and the growing use of RE sources (Gardner et al. 2022). Explainable machine learning offers a fresh outlook on model evaluation criteria, which sheds light on the future of trustworthy and explainable AI (Sun and You 2021; Gong et al. 2023; Hasan et al. 2024). It is crucial to keep interpretability and accuracy in mind when changing or creating new models. We can adopt two ways to make the SES and renewable transition model more interpretable. One is to simplify the model's structure, which might mean shortening the tree model's depth rather than lengthening it, which would sacrifice accuracy for interpretability (Barredo Arrieta et al. 2020; Ali et al. 2023b; Love et al. 2023). The alternative is to use visualization tools and post-assistance attribution analysis methods to determine the model's interpretability after training and to maintain the model's initial accuracy (Samek et al. 2019).

d. Coordinated education.

There is a persistent increase in the levels and gaps between firms because giant tech corporations control a disproportionate quantity of data and information, making it difficult for smaller companies and academics to access this data. Many obstacles must be surmounted before joint modelling can make the integration and interchange of data and knowledge a reality. The solution to the problems listed above is federated learning. Google Research was an early adopter of federated learning in 2016 (Konečný et al. 2016; Almanifi et al. 2023; Cheng et al. 2023). Joint modelling without data sharing is now possible with this technology. More specifically, no data belonging to any data owner (person, business, or institution) will ever leave the immediate vicinity. The federal system's encryption technique allows the parameter exchange method to construct a global shared model jointly, with the built model exclusively serving the local target in each region.

While distributed machine learning and federated learning share certain similarities, the two approaches are distinct in their respective areas of application, system architecture, and optimization techniques. Since distributed machine learning maintains data or model parameters on each node in an independently identically distributed (IID) fashion, it has benefits when dealing with large amounts of data and high computer resource requirements. The central server pools data and computational resources to train the model simultaneously. Due to differences in client allocations, such as time and region, federated teaching often deals with non-IID data, which means that the data is not independent and present. This section categorizes the federated learning system into its respective modules, presents an overview of the critical federated learning achievements, and delves into their potential uses in smart energy system operations and renewable transition planning. It also considers where federated learning is now. Training models with a certain amount of performance bias is possible using federated learning, which also protects data confidentiality and privacy for all parties involved, improves processing efficiency, and reduces energy usage. Two standard models for federated learning are client-server and peer-to-peer networks. To illustrate the fundamental application of a system of energy, Moayyed et al. (2022) suggested a strategy for quick forecasting of wind energy that blends combined learning with CNN approaches; this gives rise to a hybrid approach to network resilience.

A data holding and a central server typically comprise a federated learning system's physical level. Federated learning centre servers function similarly to distributed machine learning servers in that they aggregate the gradients from all data holders and then return updated gradients. To ensure data privacy in a federated learning cooperative modelling process, data holders must train their data locally only. Venkataramanan et al. (2022) used these federated learning features to propose a distributed algorithm that solves the distribution problem at the consumer level while protecting user privacy and improving accuracy. The algorithm transmits electricity generation patterns and energy consumption models without revealing consumer data. Initializing the system, doing calculations locally, aggregating data at the centre, and updating the model are the four main components of a federated learning process.

Regarding processing remote data, federated and classical distributed learning relies on the client-server architecture. However, these two approaches differ in the kinds of data they use, the properties of that data, and the makeup of the systems that employ them. Assistance for non-IID data, rapid convergence, security, privacy, and complicated user assistance are five more features of federated learning. These elements have allowed federated learning to prove its worth in many smart energy system functions. Many applications of federated learning have been studied, including flexibility forecasting, which uses aggregated demand data to build energy portfolios while protecting users' privacy. Load prediction, which uses all participating smart meters to train a single model without sharing local data, fault type diagnosis with improved generalization of models, and short-term solar energy predicting (Fekri et al. 2022, 2023; Wen et al. 2022; Perifanis et al. 2023; Abdulla et al. 2024).

e. Intelligent energy systems using computer vision

The energy sector stands to lose much from computer vision, a highly developed AI technology. Computer vision makes use of state-of-the-art tools for recognizing and processing images. Machine learning and image processing techniques, such as deep neural networks, are used to examine camera-captured images. Modern designs integrate AI vision with the IoT by moving AI processing out from the cloud and into the network's periphery (Koot and Wijnhoven 2021; Charfeddine et al. 2023; Hao et al. 2024). Connected edge devices enable on-device machine learning, paving the way for large-scale AI vision systems with impressive capabilities. Unlike most sensor technologies, reusing security cameras makes an image recognition system straightforward to deploy. The technology also leaves little to no impact on preexisting infrastructure. Therefore, these AI vision systems likewise require little maintenance. Cost-effective and capable of covering vast regions, especially in dispersed and remote locations, AI vision systems are a significant investment. Because of this, computer vision technology is well-suited for innovative energy system solutions implemented on a grand scale. Identifying anomalies, intelligent management of field people and operating behaviour, AI vision assessment and evaluation, and infrastructure related to energy detection are just a few of the many current energy technologies that use vision-based technologies. Using remote sensing photos to identify rooftop photovoltaic (PV) panels is one of the most studied areas in urban renewable distribution power sources. The use of remote sensing technologies, such as aerial and satellite photography, to determine the precise locations of already-installed PV panels is a hotly debated subject (Peters et al. 2018; Villemin et al. 2024). Segmenting solar panels using remote sensing photos, also known as solar/PV panel segmentation, has been gaining much interest since the late 2010s to improve feasible, extensible, and economically viable data-gathering methods. Early work on PV panel identification relied on statistical approaches to classify pixels according to characteristics such as colour, edge, shape, and texture; later, they found that using machine learning techniques like support vector machines and random forests improved the identification accuracy (Malof et al. 2016; Kausika et al. 2021; Le et al. 2023). Hyperspectral remote sensing photos would also help build new distinguishing features since they would better show the unique spectral properties of PV panels compared to other objects (Darwish et al. 2021; Ji et al. 2021). The accuracy and generalizability of approaches that rely on manually designed features have been severely limited because of the difficulties in accurately portraying the variety of material properties, outside conditions, and imaging conditions.

More and more, PV panel segmentation is done using deep learning algorithms like CNN, which can automatically learn and extract features from data. Even though VGGNet for PV panel detection was one of the first efforts to use deep learning for PV panel segmentation, it can tell you if the picture has PV panels or not (Malof et al. 2017; Lindahl et al. 2023). Following this, numerous deep-learning-based PV panel segmentation models could accomplish pixel-wise segmentation by utilizing complete convolution networks in various ways (Yuan et al. 2016; Sylvain et al. 2019; Jie et al. 2020). Typically, a database of solar installations for the contiguous United States has been built by Deep Solar, which combined segmentation and classification in a single convolutional neural network (CNN) (Yu et al. 2018). Many obstacles remain to overcome before deep learning-based methods can be considered genuinely robust and accurate, even though they have been more successful than previous approaches in producing somewhat trustworthy segmentation results (Li et al. 2021;

Guo et al. 2023b). These include, but are not limited to, significant panel size variances, unequal sample distributions, homogeneous textures, and heterogeneous colours. Computer vision has been helpful in the energy sector, where it has simplified system operations. To ensure that wind farms run smoothly while protecting endangered birds from wind turbine blades, machine vision solutions are provided by Phil-vision GmbH and Stemmer Imaging (Woodman et al. 2023). To save endangered birds and cut down on costly turbine shutdowns, a computer vision system trained with 500,000 images uses deep learning to identify and follow the flight paths of large birds of prey. The goal is to turn off wind turbines only when birds within a certain distance approach them. The oil and gas industry has also used computer vision, including non-destructive inspection, system corrosion analysis, safety monitoring, maintenance, and service life prediction (Ma 2023; Nathanail 2023). Powerhouse industrial conglomerates like ABB, Siemens, and GE have used AI-powered computer vision to enhance the energy efficiency of their client services and operations, focusing on the demand side of energy systems (Voulodimos et al. 2018; Ferré Gras 2023; Ciranni et al. 2024).

4. Examples of use and demonstration

Industry use cases have been sparked by the numerous research projects that have examined the integration of SES, energy transition, and developing computing, information, and communication technologies. Smart energy system design, analysis, prediction, and operation are all areas where AI-based technologies shine. Compared to traditional computer systems, quantum computing offers significant computational cost savings when dealing with complicated challenges in SES. Opportunities for economic growth arise due to blockchain technology's novel energy trading methods and its integration of crypto-assets with energy networks. The decarbonization and operation of SES can be facilitated by 5 G/6 G's enhanced responsiveness and connectivity. When handling large amounts of data, AI-based solutions can significantly improve energy transition planning and smart energy system management. To combat the shadow effects of wind turbine wakes and recover energy through wake steering. Utilizing the compelling computing facilities of Microsoft Azure and the controller development platform DeepSim, which is based on reinforcement programming, Vestas utilizes AI for simulating and controlling (Leal Filho et al. 2024; Satornino et al. 2024). For energy systems to run smoothly, prediction and uncertainty are paramount. Argonne National Laboratory uses supervised and unsupervised learning techniques to inform more dependable grid planning and operations while using more computationally efficient methods than conventional approaches (Zhao et al. 2023).

Artificial intelligence (AI)-based solutions have the potential benefit of eliminating the computational process that typically precedes decision-making in energy systems planning, which can be somewhat time-consuming (hours or days). As an alternative, AI models are pre-trained using massive data, and judgments can be immediately achieved by altering the modelling input. Though there are many benefits to SES that integrate AI, several concerns must be resolved before widespread use. These concerns include the effects of AI on long-standing practices, regulatory frameworks, and the dependability of the systems themselves (Wenskovitch et al. 2022). Some real-world examples show how new technologies like 5G/6G, blockchain, and quantum computing can be used in SES. In quantum computing, IBM collaborated with a German utility to investigate potential quantum-based solutions to the increasingly decentralized energy workflow. These solutions could address optimization issues related to large-scale, complex energy procurement, trading, and hedging, challenging classical computing systems (Karthik et al. 2023; Ramouthar and Seker 2023a, b). Microgrid implementations in Brooklyn and Australia show that blockchain opens the door to new ways of thinking about the interaction between prosumers, customers, utility providers, and decentralized SES regarding trade (Gifford 2016; Mahmoudian Esfahani 2022). In addition, Texas applications note that blockchain-based crypto-assets can provide economic opportunity to reap the benefits of green energy efficiency (House 2022; Zhang et al. 2023a). Chinese SES have begun using 5 G for communication, which brings many benefits, such as intelligent peak shaving, smart voltage boosting, and efficient energy storage (Dongxu 2020). Moreover, as Ericsson noted, 5 G will have a rapid and catalytic effect on lowering CO2e emissions across Europe (Drubin 2021).

5. Outlook for Renewable Energy

While new ICTs have shown promise in many areas, including SES design and scheduling, there are still gaps in our understanding of fully integrating these technologies with the energy industry. It would be prudent to investigate methods to make cryptocurrency a more environmentally friendly part of future deep decarbonized SES, to attain high penetration levels of RE and maintain sustainable system operations, considering the increasing worries about the loss of RE and the climate impacts of digital asset trading associated with blockchain technology. There have been investigations into potential new methods of cryptocurrency mining that are less harmful to the environment and can considerably reduce the operational load on energy systems (Gong and You 2015; Li et al. 2023; Meke and Dincer 2024). One example is the increasing use of wind power in electric power systems. New wind farms, which are already contributing significantly, may use their electricity to mine bitcoins instead of waiting for production to begin (Bastian-Pinto et al. 2021). Here, bitcoin mining profits can cover wind farms' anticipation expenses and provide a safety net for energy providers who would otherwise have to deal with the uncertainty of the spot market when selling their power. Thus, linking bitcoin mining to building renewable power-generating facilities encourages early investment and the shift toward SES that do not produce carbon. Electric power market grid-level services can be valuablely supplied by cryptocurrency miners (El Helou et al. 2022; Menati et al. 2023). Optimal system coordination allows for the deployment of cryptocurrency miners to absorb the unpredictable fluctuations in energy supply while also providing flexibility to the demand side. Reduced electricity prices are reasonable for electric power networks, and miners can earn money by offering grid services and bitcoin rewards. Thus, in the future SES, it could benefit both cryptocurrency mining businesses and system operators if miners actively participate in demand response programs.

Future energy systems that heavily include RE sources present new avenues for investigation as cryptocurrency mining becomes more integrated into these systems. To illustrate the importance of crypto mining for SES at the national or state level over the next decade. Economic income from cryptocurrency mining, power grid ancillary services, and the use of wasted renewable or fossil energy are all important metrics to consider when analyzing the pros and cons of this integration. Researchers face two obstacles to determining if cryptocurrencies can be used in SES in the long run. From monetary gains, system dependability, energy waste reduction, and environmental effects to effects on the environment, the first hurdle is to compare the impact and efficiency of bitcoin mining in SES to traditional energy storage systems. Another obstacle is figuring out how to work with energy storage solutions and bitcoin mining to power future energy systems. This will require research into the environmental and energy effects of various crypto-mining capacities and penetration levels of RE sources. Research in this area can help us better understand the long-term impacts of cryptocurrency mining incentives and the elasticity of electricity demand from these activities. This could lead to SES that are more economically efficient and more reliable on the grid. In contrast to the valuation of traditional energy management methods, which considers a wide range of ancillary services, it shows the pros and cons of bitcoin mining in SES. There is a need for more investigation into the effects of cryptocurrency mining on SES at the national or state level, specifically how it can hasten the shift to renewable power, improve demand response times, cut down on fossil fuel waste, and make better use of renewable power cuts and off-grid solar or wind farms.

6. Conclusion

Reducing carbon in the energy system is critical to mitigating global warming, with the power industry significantly contributing to releasing greenhouse gases into the atmosphere worldwide. Emerging information and communication technologies are playing a pivotal role in the energy sector, enabling the design and operation of future intelligent energy systems with greater integration of RE. This advancement helps address the two main challenges in reducing carbon in the energy system: planning for a RE transition and ensuring sustainable system operation. Considering the recent shift toward RE sources, this study assesses ICT's most recent scholarly work and practical uses in SES. The technologies reviewed in this study can be classified into artificial intelligence (AI)-based and non-AI technologies. SES incorporates AI-related technologies such as optimizing, analyzing time series, learning by association, machine vision, explainable AI, and trustworthy AI. Blockchain, quantum computing, the future of messaging systems, and the metaverse are non-AI information and communication technologies that assist with the system's operations and the shift to RE. Regarding non-AI technologies, quantum computing has distinct benefits in intelligent energy systems because it can solve complicated issues that traditional computing systems find computationally expensive.

Integrating crypto-assets into future SES might provide economic advantages, and blockchain technology could provide the groundwork for new energy trading methods. Improved responsiveness and connectedness made possible by next-generation technology for communication could lead to more effective and smarter running of the power systems, which in turn could lead to a significant share of RE and higher sources of energy distributed. Due to its potential for broad acceptance and its profound alterations to many socioeconomic activities, the developing metaverse industry could substantially affect the design and management of SES in the following decades. SES has shown beneficial use of AI-related technology in several academic and industrial contexts. Optimization can lessen the monetary burden of planning to transition to RE sources and operating energy systems. Integrating time series and sequence-to-sequence learning into smart sensors is a great way to monitor energy consumption and make accurate predictions for SES. This could lead to scalable solutions. Energy system operators have found several uses for federated learning, such as understanding collective power consumption patterns without disclosing individual power traces and creating privacy-preserving energy portfolios using aggregated demand data. SES also heavily used computer vision, which safeguarded wind turbine blades and ensured that wind farms ran smoothly by supplying location data for renewable generation. Quantifying and explaining basic features of power system operation and stability could be aided by trustworthy AI based on recent machine learning algorithms.

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.

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