Challenges and Pathways of Low-carbon Oriented Energy Transition and Power System Planning Strategy: A Review

Jing Qiu, Junhua Zhao, Fushuan Wen, Junbo Zhao, Ciwei Gao, Yue Zhou, Yuechuan Tao, Shuying Lai

***Abstract*— This paper provides an overview of the challenges and pathways involved in achieving a low-carbon-oriented energy transition roadmap and power system planning strategy. The transition towards low-carbon energy sources is crucial in mitigating the global climate change crisis. However, this transition presents several technical, economic, and political challenges. The paper emphasizes the importance of an integrated approach to power system planning that considers the entire energy system (including both physical and information systems and market mechanisms) and not just individual technologies. To achieve this goal, the paper discusses various pathways toward low-carbon energy transition, including the integration of renewable energy sources into current energy systems, energy efficiency measures, and market-based and regulatory strategies encompassing the implementation of regulations, standards, and policies. Furthermore, the paper underscores the need for a comprehensive and coordinated approach to energy planning, taking into account the socio-economic and political dimensions of the transition process. In addition, the paper reviews the methodologies used in modeling low-carbon-oriented power system planning, including both model-based methods and advanced machine learning-assisted solutions. Overall, the paper concludes that achieving a low-carbon-oriented energy transition roadmap and power system planning strategy requires a multi-dimensional approach that considers technical, economic, political, and social factors.**

***Index Terms*—Energy transition, low-carbon-oriented power system planning, renewable energy integration, socioeconomic and political dimensions.**

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J. Qiu, Y. Tao, and S. Lai, are with the School of Electrical and Information Engineering, The University of Sydney, Sydney, NSW 2006, Australia. (Email:ytao5383@uni.sydney.edu.au)

J. Zhao is with the School of Science and Engineering, The Chinese University of Hong Kong, Shenzhen, Shenzhen, 518100, China, and also with the Shenzhen Institute of Artificial Intelligence and Robotics for Society, Shenzhen, 518100, China. (zhaojunhua@cuhk.edu.cn)

F. Wen is with the School of Electrical Engineering, Zhejiang University, Hangzhou, 310058, China.

J. Zhao is with the Department of Electrical and Computer Engineering, University of Connecticut, Storrs, CT 06269 USA (junbo@uconn.edu)

C.Gao is with the Department of Electrical Engineering, Southeast University, Nanjing, Jiangsu 210096, China (ciwei.gao@seu.edu.cn).

Y. Zhou is with the School of Engineering, Cardiff University, Cardiff CF24 3AA, U.K. (zhouy68@cardiff.ac.uk).

I. Introduction

The energy sector is currently facing a critical challenge in meeting the growing energy demand while also reducing greenhouse gas emissions and mitigating the impacts of climate change. The transition towards low-carbon energy sources has become a pressing issue, requiring a comprehensive approach that includes the deployment of renewable energy technologies and their integration into existing energy systems. The energy transition is a complex process that involves multiple stakeholders, including governments, utilities, industry, and consumers, and requires significant investments in new infrastructures and technologies.

Power system planning is a crucial component of the energy transition and plays a vital role in determining the capacity, location, and interconnection of power generation as well as transmission and distribution assets. The primary goal of power system planning is to ensure a reliable and cost-effective energy supply while taking into account the energy mix, system flexibility, and security of supply. The process of power system planning involves minimizing investment and operation costs, balancing the conflicting objectives of reducing greenhouse gas emissions, increasing the use of renewable energy sources, and maintaining system reliability and operation security.

Renewable energy sources, including wind, solar, and hydropower, are crucial elements of the low-carbon energy transition. These sources are anticipated to fulfill a substantial portion of the world's future energy demand. However, the integration of renewable energy sources into the existing energy systems presents a complex and formidable challenge, necessitating significant changes to current infrastructure and technology. A primary obstacle in integrating renewable energy sources is their variable and uncertain nature. To address this issue, the development of new technologies and strategies is essential for effectively managing the integration of renewable energy into the power system.

One method of power system planning involves adopting a centralized model, wherein a single organization takes responsibility for both planning and operating the power system. This approach has been used in many countries and demonstrates its effectiveness in providing a reliable and cost-effective energy supply. However, this approach also has its limitations, as it may exhibit bureaucratic tendencies, display slow responsiveness to fluctuating market conditions, and potentially restrict the involvement of new participants in the energy sector.

An alternative approach involves adopting a decentralized model in which numerous stakeholders participate in the planning and operation of the power system. This method offers more flexibility and responsiveness to evolving market conditions and enables the inclusion of new entrants in the energy sector. However, the decentralized model also presents challenges, such as the potential for a fragmented energy market and the difficulty of coordinating actions among multiple actors.

Integrating renewable energy sources into existing energy systems necessitates the development of innovative technologies and strategies for managing their incorporation into the power system. For instance, energy storage systems can be employed to store surplus energy generated by renewable sources, which can later be utilized to meet energy demand during periods of high load demand and low renewable energy generation. Additionally, advanced control systems can facilitate the integration of renewable energy sources into the power system by regulating the flow of energy between these sources and the energy grid.

The development of smart grid technology is a crucial aspect of the low-carbon energy transition and the integration of renewable energy sources into an existing power system. Smart grids are designed to offer increased flexibility and responsiveness to evolving market conditions, enabling the efficient and cost-effective incorporation of renewable energy sources into the power grid. Moreover, smart grids facilitate the integration of energy storage systems, advanced control systems, and other essential technologies for seamlessly incorporating renewable energy sources into established power systems.

In summary, the low-carbon energy transition and power system planning are intricate and demanding tasks that necessitate the involvement of multiple stakeholders, as well as the development of advanced technologies and strategies. The energy transition is a vital component in combating climate change and calls for substantial investments in new infrastructure and technology. In this review, we thoroughly analyze the drivers, challenges, and pathways toward energy transition and low-carbon-oriented power system planning from political, technological, and societal perspectives. Furthermore, we examine the methodologies employed in state-of-the-art works to address low-carbon power system planning.

II. Drivers of Low-Carbon-Oriented Energy Transition

The low carbon-oriented energy transition is a critical aspect of the global response to climate change and the associated environmental risks. The need for this transition is driven by the increasing demand for energy and the associated greenhouse gas emissions, which are major contributors to climate change. In this paper, the drivers of the low carbon-oriented energy transition will be analyzed from four aspects, i.e., policy, legislation, technology, and financial support.

A. Policy and Legislation

Policy and legislation play a significant role in driving this transition by creating an enabling environment for the deployment of renewable energy technologies and reducing the use of non-renewable energy sources.

Carbon pricing mechanisms, such as carbon taxes and cap-and-trade systems, are among the most effective policy tools for encouraging the reduction of greenhouse gas emissions [1]. Carbon taxes put a price on carbon emissions and provide a financial incentive for reducing emissions [2], while cap-and-trade systems set a limit on the amount of carbon emission that can be released into the atmosphere and allow companies to trade emissions allowances [3], shown as Fig. 1. The cap-and-trade system is also known as the emission trading system (ETS), which has been put into operation in some countries and regions around the world, including the European Union Emissions Trading System (EU ETS) [4] and the Regional Greenhouse Gas Initiative (RGGI) in the United States [5]. Both of these mechanisms create a financial incentive for concerned entities to reduce their carbon footprint and transition to low-carbon energy sources. However, the effectiveness of these systems has been the subject of much debate, and there are ongoing discussions about how to improve and expand their impact.

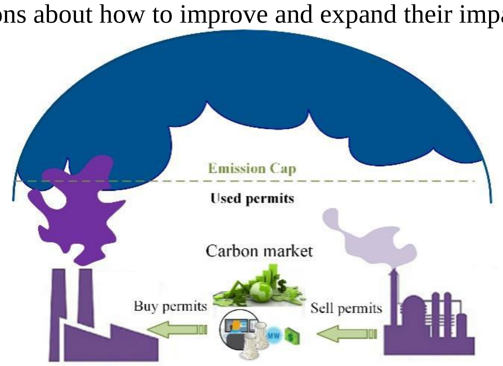

Fig. 1. Carbon trading scheme.

Renewable energy targets are another important policy tool for driving the low-carbon energy transition. Renewable energy targets set a goal for the proportion of energy that must come from renewable sources, such as wind, solar, and hydropower [6]. This helps to create a stable and predictable policy environment that is conducive to investment in renewable energy technologies. According to [7], formulating proper renewable portfolio standards can effectively increase the share of renewable energy power, lead to renewable resource diversity, and further control emissions. Renewable energy targets also help to drive innovation and encourage the development of new technologies as companies compete to meet the target. However, it is argued that the future energy infrastructure we build may also bring negative effects, such as reduced biodiversity due to land-use change [6].

The low-carbon energy transition is also driven by international cooperation and collaboration. Governments around the world are working together to promote the deployment of renewable energy technologies and reduce greenhouse gas emissions. This includes the negotiation of international agreements, such as the Paris Agreement [8], which sets a global target for reducing emissions and provides a framework for international cooperation on climate change.

B. *Technology*

The rapid development of renewable energy technologies, such as wind, solar, and hydropower, has made it possible to integrate these technologies into existing power systems [9]. Offshore wind and floating solar technologies have the potential to generate large amounts of electrical energy, making them suitable for large-scale deployment. They also have the advantage of being located away from densely populated areas, reducing the potential for conflicts with other purposes of land use. The increasing affordability and efficiency of these technologies, combined with the declining cost of energy storage, has made it possible to store excess energy during periods of high generation and use it during periods of high demand or low generation. This helps to overcome the variability of renewable energy sources by smoothing the intermittent renewable energy outputs and allows for a more stable and reliable power supply [10].

The smart grid is another key technology for enabling the integration of renewable energy sources into existing power systems. The smart grid represents a modernized electrical grid, which makes a conventional grid more controllable and greener, as well as improves the delivery of power. The present revolution in communication systems, particularly stimulated by the internet, offers the possibility of much stronger monitoring and control capability throughout the power system, and hence, more effective, flexible, and lower-cost operation [11]. The smart grid provides an opportunity to transform electrical power systems through the implementation of new Information and Communication Technologies (ICTs). The realization that ICT can play a significant role in modernizing the management of electrical networks has coincided with the understanding that reducing carbon emissions in the power sector can only be achieved cost-effectively with proper monitoring and control. Furthermore, various factors have now converged to generate interest in the smart grid.

Some new technologies for reducing energy consumption have also played a critical role in driving the low-carbon energy transition. Energy efficiency technologies, such as building insulation [12] and efficient lighting [13], help to reduce energy consumption and lower greenhouse gas emissions.

The development of new technologies and business models has also driven innovation and investment in the low-carbon energy transition. For example, community energy projects and peer-to-peer energy trading have created new opportunities for investment and the deployment of renewable energy technologies [14, 15].

C. *Financial Support*

Financial support drives the low-carbon-oriented energy transition by providing the resources necessary for the development and deployment of renewable energy technologies. Governments and private organizations have introduced a range of financial incentives to encourage investment in renewable energy technologies. Tax credits and subsidies are two of the most common financial incentives [16]. Tax credits provide a direct reduction in the amount of taxes owed, while subsidies, as mentioned before, provide direct financial support for the development and deployment of renewable energy technologies. Subsidies for renewable energy technologies are also a critical policy tool for driving the low-carbon energy transition. Subsidies provide financial support for the development and deployment of renewable energy technologies, making them more affordable and accessible [17]. For example, the government provides subsidies to individual PV investors when their PV systems are installed by estimating the total emission reduction within the life span of the devices. This helps to overcome the initial costs associated with the deployment of renewable energy technologies and encourages the widespread adoption of these technologies. However, when the number of end-users with distributed renewable energy increases dramatically, the value of subsidies becomes a heavy financial burden to the local government. Hence, renewable energy certificates (RECs) are designed to reduce direct subsidies from the government. With the REC mechanism, electricity consumers actively subscribe to green power [18]. Some companies and organizations will purchase RECs to demonstrate their commitment to using renewable energy and reducing their carbon footprint so that their international reputation can be promoted [19]. Both of these financial incentives help to overcome the initial costs associated with the deployment of renewable energy technologies and encourage the widespread adoption of these technologies. The development of new financial instruments, such as green bonds, has also played an essential role in attracting investment in the low-carbon energy sector. Green bonds are issued specifically to finance projects with environmental benefits, such as renewable energy projects [20].

In addition to financial incentives, governments and private sector organizations have also introduced financing mechanisms to support the low-carbon energy transition. This includes the establishment of dedicated funds and financing institutions, such as the Green Climate Fund, which provides financing for low-carbon energy projects in developing countries [21].

The growth of the renewable energy sector has also created new investment opportunities for private investors. Renewable energy projects, such as wind and solar farms, offer the potential for long-term, stable returns, making them attractive investment opportunities for private investors.

III. Challenges of Low-Carbon-Oriented Energy Transition and Power System Planning

A. *Socio-economic Challenges*

One of the largest challenges for the low-carbon-oriented energy transition and power system planning is the cost involved.

The transition to a low-carbon power system can be expensive, particularly in the short term. This can present a challenge for governments and private organizations, who must find the resources to finance the transition. Therefore, looking for a proper transition roadmap [22], where the investment portfolio and construction plan should be properly designed, becomes essential.

The economic challenge is a segment in the energy trilemma, i.e., energy security (risk), energy sustainability (environment), and energy affordability (cost) [23]. The development of a regulatory framework that supports the transition to a low-carbon power system should fully consider the energy trilemma. Balancing these three priorities is a huge challenge, as they often conflict with each other. For example, increasing energy security may require the use of non-renewable energy sources that have negative environmental impacts. The deployment of the energy storage system for mitigating intermittent renewable energy power output to ensure energy security will inevitably increase the financial budget. The energy trilemma highlights the need for integrated, long-term planning and decision-making in the energy sector to ensure that energy security, sustainability, and affordability are all given due consideration [24]. It also highlights the need for a transition to a more sustainable power system, which relies on renewable energy sources and energy efficiency and minimizes the negative impacts of energy production and use.

Besides, the deployment of renewable energy technologies, such as wind and solar farms, can sometimes be met with resistance from local communities, who may have concerns about the visual impact of these technologies or the potential loss of land and property values. This can present a challenge for governments and private organizations, which must engage with local communities and address their concerns.

The transition to a low-carbon power system can also present challenges for employment and skills, as the energy sector shifts from traditional energy sources to renewable energy technologies. This can require the retraining and upskilling of workers in the energy sector.

B. Technical Challenges

Some of the key technical challenges are detailed below.

Integration of renewable energy sources: The integration of renewable energy sources, such as wind and solar, into existing energy systems can present technical challenges, such as the variability of renewable energy sources and the need for energy storage solutions. These challenges must be addressed in order to ensure a stable and reliable energy supply. According to [25], the integration of variable renewable energy brings challenges in balance, quality, and flow. The balance problem results from insufficient short-term generation [26], insufficient long-term generation [27], insufficient firmness of variable renewable energy [28], and inaccurate forecast of the variable renewable energy output [29]. These growing inequalities between supply and demand are mainly caused by changes in the generation mix, which contains growing variable renewable energy generators with limited dispatch-ability. Besides, the integration of renewable energy may also jeopardize the power quality, including increased flicker [30], stepping up harmonic distortions [31], unstable shutdown at blackout [32], and increasing excursion at local voltage [33]. The increased flicker and stepping up harmonic distortions are mainly caused by electronic power inverters of the variable renewable energy generators, and it will affect the life span of the equipment at end-users. Also, the integration of renewable energy will result in changes in power flow patterns, such as bi-directional power flow in the distribution network [34]. The inadequate preparation for such changes will result in a shorter lifetime or damage to transmission equipment and distribution, as well as increasing loss.

Grid stability: The integration of renewable energy sources into existing power systems can also impact grid stability. The cause of the stability problem is the modularity of the variable renewable energy (VRE) generator and the synchronization of the generator. The power grids face increased stabilization breaches, dispatch or limitations due to stability apprehension [25]. The stability problem includes frequency stability, voltage stability, transient stability, and dynamic stability. Apart from these conventional stability problems, the large-scale renewable penetration may further cause new stability issues, such as electromechanical-like low-frequency oscillation, electromagnetic wideband oscillation, and new large-disturbance instabilities [35]. The reasons that cause these stability problems mainly include the insufficient supply of reactive capacity [36], reducing short-circuit current [37], reducing inertia [38], weak immunity to frequency and voltage deviations (failure to manage frequency travel limits, diminishing reserves of frequency control and insufficient synchronization of the voltage trip limits) [39, 40], resource intermittency [41], etc. To further solve the stability problem, it requires the development of new technologies, such as smart grid systems, to manage the integration of renewable energy sources into existing power systems.

Energy storage: Energy storage solutions, such as battery storage and hydro pump, play an important role in the system with high penetration of renewable energy, as they allow for the storage of excess energy generated during periods of high renewable energy generation and its use during periods of low renewable energy generation [42]. The battery energy storage system (BESS) is believed to be promising for its fast response to provide various services, such as frequency regulation [43]. However, at the current stage, the BESS is still very expensive in its investment and maintenance process, making it challenging to achieve cost-effectiveness. Apart from the BESS technology itself, the BESS management strategy also becomes a critical aspect to be focused on. Due to the lifespan of the battery, the BESS management strategy should consider the battery degradation cost [44] and state-of-health (SOH) [45], reducing the capacity and efficiency. Further considering the battery health, the second-life usage of the BESS becomes a new topic to be discussed [46]. Besides, to integrate the BESS into the current power grid, the control systems and communication networks also face updates.

Interconnections: The interconnection between the renewable power system and the current system is another key technology. The interconnections include the connection between transmission networks and distribution networks [47], the microgrids and main grid [48], as well as the electricity network and the other integrated networks [49]. As the use of renewable energy sources grows and new transmission and distribution technologies are developed, there has been a trend toward connecting multiple electric power grids around the world. This has resulted in complex systems with multiple energy grid connections, a mix of AC and DC transmission/distribution networks, and the presence of multiple power producers and market entities. These changes have had a significant impact on the topology and stability of the system.

Cybersecurity: The integration of renewable energy sources into existing power systems requires advanced control and communication system to support, which arouse the cybersecurity problem [50]. Lack of cybersecurity technologies will lead to the data theft of sensitive information and cyber-attacks, including false data injection and Denial of Service (DoS) attacks [51]. These problems will compromise the security and stability of the system and even cause the paralysis of the whole system. Therefore, ensuring the security of the power system is critical for the success of the low-carbon energy transition. To address these cybersecurity risks, cybersecurity risk assessments, encryption, blockchain technologies, and incident response plans can be formulated [52].

C. *Environmental Challenges*

Another practical challenge to realize the power system transition is environmental challenges, considering land use, biodiversity, resource depletion, water use, and waste management [53].

The deployment of renewable energy technologies, such as wind and solar farms, can impact land use, particularly in areas where there is limited available land [54]. The deployment of renewable energy technologies can also impact biodiversity, particularly if they are deployed in areas of high biodiversity value. This can require the careful planning and management of renewable energy projects to minimize their impact on the environment and local ecosystems.

The production of renewable energy technologies, such as wind turbines and solar panels, can also impact resource depletion, as they require the use of finite resources, such as metals and minerals [55, 56]. This can require the development of sustainable resource management practices and the use of recycled materials in the production of renewable energy technologies.

The production of some renewable energy technologies, such as hydropower, can also impact water use, as they require large amounts of water for their operation. This can require the careful management of water resources and the use of alternative technologies, such as wind and solar, in areas where water is scarce [57].

The end-of-life disposal of renewable energy technologies, such as wind turbines and solar panels, can also impact the environment, as they require the safe disposal of waste materials [57]. This can require the development of effective waste management practices and the use of recycled materials in the production of renewable energy technologies.

IV. Pathways for Low-Carbon-Oriented Energy Transition and Power System Planning

A. *Technological Pathways*

1) *Renewable energy technologies*

Renewable energy technologies, including wind, solar, hydropower, and geothermal, are critical for the transition to a low-carbon power system. These technologies can help to reduce greenhouse gas emissions and increase the use of clean and sustainable energy sources. The deployment of renewable energy technologies can also help to increase energy security, as they are not dependent on finite fossil fuel resources. In future pathways for low-carbon-oriented power system planning and energy transition, the development of distributed renewable energy resources is the main trend. In the current research, the integration requirement and control method for the distributed generators (DGs) from renewable energy sources have been focused on [58]. These methods are established to ensure grid stability, including voltage stability, frequency stability, voltage ride-through (VRT), power quality, and active and reactive power regulations [59]. The placement and sizing problems of the DGs from renewable energy sources (RESs) are usually solved through an optimization approach by using analytical approaches, intelligent search methods, heuristic methods, iterative methods, and gradient and second-order methods [60]. When formulating the operation and planning strategies of the DGs, the uncertainty problem of the RESs should be taken into consideration.

2) *Energy storage*

Energy storage solutions, such as battery storage, are critical for the integration of renewable energy sources into existing power systems. It helps to ensure a stable and reliable energy supply by providing voltage and frequency regulation services, even during periods of low renewable energy generation. BESS has some advantages over conventional energy sources, which include fast and steady response, adaptability, controllability, environmental friendliness, and geographical independence, and it is considered as a potential solution to the global warming problem [61]. For the BESS planning and operation optimization problem, the objective function is usually designed from the view of BESS cost [10], BESS capacity and lifespan [62], and power quality [63], considering the constraints of charging and discharging limits, capacity limits, state-of-charge (SOC) balance, SOC limits, and environmental constraints. Apart from the conventional stationary BESS, the mobile energy storage system (MESS) is a new technology in the current literature [64]. In recent years, with the process of transportation electrification, the concept of mobile power sources has emerged. Compared with stationary energy storage systems (SESS), the mobility of mobile power sources enhances its capability of tapping into multiple value streams that have spatiotemporal variability, which in turn improves its asset utilization and potentially its value proposition [65]. Hence, the dispatch strategy of mobile power sources has become an emerging and promising topic [66].

3) *Smart grid*

Smart grid technologies are developed for the integration of

RESs and ESS into existing power systems. Smart grid systems allow for the efficient and effective management of the power system by enabling the real-time monitoring of energy generation and consumption. The regarding technologies include Internet-of-things (IoTs), cyber-physical systems (CPS), Energy Internet (EI), etc. The IoT refers to a network of physical devices, vehicles, home appliances, and other items embedded with electronics, software, sensors, and connectivity, which enables these objects to collect and exchange data [67]. The IoT allows physical objects to be connected and controlled remotely across existing network infrastructure, creating opportunities for more direct integration between the physical world and computer-based systems, leading to improved efficiency, accuracy and economic benefit. Some common applications of IoT in smart grids include smart homes with IoT-enabled devices, such as smart thermostats, smart locks, and smart lighting, Advanced Metering Infrastructure (AMI) that can provide real-time data on energy consumption, distribution automation devices such as IoT-enabled sensors and control systems, IoT-enabled vehicles that can collect and exchange data on driving patterns, traffic conditions, and vehicle performance, and etc.

CPS, on the other hand, refers to systems that integrate physical processes with computer-based systems and networks, enabling the real-time control and monitoring of physical processes, as shown in Fig. 2. In the context of smart grids, CPS can be used to improve the operation and management of the power grid, enabling real-time control and monitoring of the power grid and enabling the integration of advanced communication and information technologies with physical processes [68]. The IoT provides the connectivity and data collection capabilities that enable smart grids, while CPS provides the advanced control and monitoring capabilities that improve the efficiency, reliability, and sustainability of the power system.

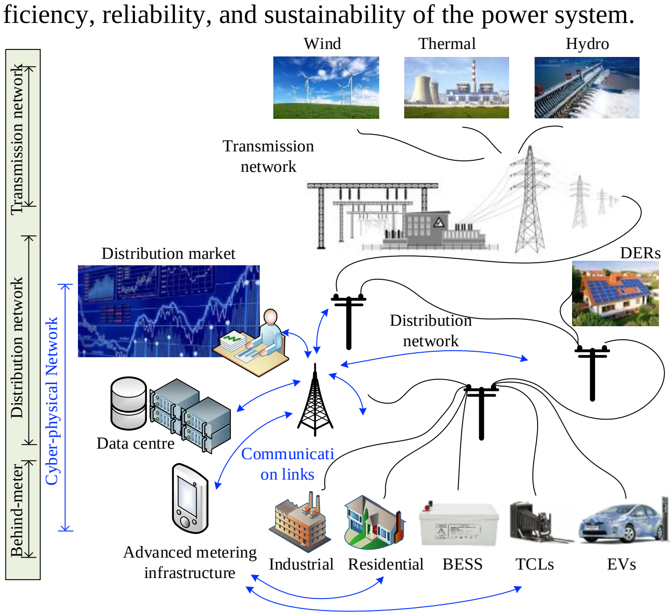

Fig. 2. Smart grid structure from the view of the cyber-physical system.

The EI refers to a conceptual framework for the future of the power system, in which the traditional centralized power generation and distribution model is replaced by a decentralized, interconnected network of energy producers and consumers [69]. The EI aims to create a more flexible, efficient, and sustainable power system, enabling the integration of renewable energy sources, energy storage, and energy-efficient technologies [70].

4) Electrification

Electrification is a key technological pathway for low-carbon-oriented power system planning and transition. It involves increasing the use of electricity in various sectors, such as transportation, heating, and industry, as a means of reducing greenhouse gas emissions. The idea behind electrification is that electricity can be produced from low-carbon sources, such as wind, solar, and hydropower, and that electric vehicles, heat pumps, and other electric technologies are more efficient and emit less carbon compared to their fossil fuel counterparts.

Transportation electrification has been hotly discussed and widely investigated [71]. Electric vehicles (EVs) have attracted increasing attention as green transportation. To ensure the popularization of EVs in future transportation systems, sufficient EV energy supplement infrastructures should be invested [72]. Despite the fact that EVs do not emit pollutants while driving, their increasing demand for electricity may result in an increase in emissions from the electricity system if more fossil fuels are used to meet the growing demand. Fast charging stations (FCSs) also contribute to emissions. While EVs can reduce per-kilometer petroleum use [73], this does not necessarily equate to a reduction in carbon emissions, which require additional efforts. In regions where coal-based power is dominant, hybrid electric vehicles (HEVs) are a better option for reducing CO2 emissions compared to plug-in hybrid electric vehicles (PHEVs) or battery electric vehicles (BEVs). However, HEVs do not interact with the power grid and refuel with gasoline like traditional internal combustion vehicles. The improved fuel efficiency of HEVs leads to reduced emissions. This study focuses on modeling BEVs and PHEVs and finds that in regions dominated by coal power, the emission reductions achieved by EVs are limited. The increasing demand for electricity from EVs tends to increase emissions from fossil fuel-fired power generators. Thus, the future trend is to run EVs on zero- or low-carbon electricity [74]. The comprehensive study of overall emissions in both transportation and electricity systems requires collaboration between the electricity distribution network and transportation system planning [75].

However, electrification also presents challenges for power system planners and policymakers. For example, the increasing EV charging demand may put pressure on the grid, requiring investments in new transmission and distribution infrastructure. The access of large-scale EVs to the grid using a disorder charging strategy will jeopardize the electricity services of power systems, such as voltage deviation and extra power loss, especially during peak hours. Therefore, a coordinated EV charging strategy is essential to transportation electrification and low-carbon-oriented power system planning [76]. To deal with these problems, off-peak charging, valley-filling charging, and smart charging were proposed [77, 78]. Individual EV power capacity is too small to affect the entire system operation. Therefore, it is necessary to aggregate EVs to make them compatible as a concise collection of power ramping controls. The aggregated

EVs can provide regulation services [79].

5) Interconnection

The future power grid is a sustainable, smart and complex grid, which contains multiple sub-systems. With the penetration of DGs from RESs and BESS in the distribution network, the conventional passive distribution network is transformed into the active distribution network (ADN). The interconnection between the ADN and the transmission network is critical for the efficient operation of the power system. The ADN provides real-time data on local energy demand and generation, enabling the transmission network to adjust its operations to meet the changing demand. At the same time, the transmission network provides the necessary capacity to support the integration of renewable energy sources into the ADN. The interconnection between the ADN and the transmission network also enables the integration of distributed energy resources, such as rooftop solar panels and energy storage systems, into the overall power system, improving the reliability and sustainability of the power system. Considering the interaction between the transmission system and ADN can formulate a solution that maximizes the total social welfare can be selected from several available alternatives for the line expansion as well as fossil-fuel and renewable-based generator expansion at both system levels [80].

Microgrids also play a critical role in the integration of renewable energy sources into the overall power system, improving the reliability and stability of the power grid. By operating locally, microgrids can reduce energy transmission losses and improve the efficiency of the power system. In addition, microgrids can provide greater energy security and resilience, enabling communities to continue to access energy even in the event of natural disasters or other disruptions to the main power grid. The interconnection between microgrids and the main grid requires advanced AC/DC, DC/CD and AC/AC energy conversion technologies.

Besides, the interconnection between multiple energy networks, such as electricity, heating, and gas, makes the whole system more complex. This type of system enables the efficient and sustainable use of energy resources, improving the overall efficiency, flexibility and sustainability of the power system. As a clean fuel source, natural gas plays an important role in achieving a low-carbon economy in the power industry. Owing to the uncertainties introduced by the increasing utilization of natural gas in electric power systems, gas systems and power systems should be planned in an integrated manner [81]. When considering these two systems simultaneously, there are many emerging difficulties, e.g., increased system complexity and risk, market timeline mismatch, overall system reliability evaluation, etc. [82, 83].

6) Cybersecurity

Apart from the interconnection between physical networks, the interconnection between communication networks and the physical systems in a CPS is also essential to ensure the operation of the complex system. As the power system becomes increasingly interconnected and reliant on advanced technologies, such as smart grid systems, the risk of cyber-attacks and data breaches increases, posing a threat to the stability and reliability of the power system. To ensure the security of the power system, it is important to implement robust cybersecurity measures. Several relevant technologies should be focused on. First, secure data management involves protecting sensitive energy data, such as energy generation and consumption data, from unauthorized access and tampering. Second, secure communication networks should be developed to implement secure communication networks, such as encrypted communication protocols, to protect energy data and control systems from cyber-attacks. Third, a cybersecurity risk assessment should be conducted to identify and assess the risks posed by cyber-attacks and implement measures to mitigate these risks. Fourth, training and education should be provided to power system employees on cybersecurity best practices, including secure data management and secure communication protocols. Fifth, cybersecurity incident response should be designed to respond to a cybersecurity incident, including identifying the source of the attack and restoring the power system to normal operation.

B. Market-Based Pathways

1) Carbon pricing

As mentioned, carbon pricing mechanisms provide a financial incentive for reducing greenhouse gas emissions by putting a price on carbon emissions. To control the emissions produced by primary energy consumption, such as coal, a quota is allocated to each thermal generator to restrict its annual carbon emission. Some generators can finish the task, and they can sell surplus quotas, while other generators cannot fulfill the mission and must buy extra quotas. In the literature, the carbon market and carbon trading have been studied. The relevant topics include the trading mechanism [84], emission permit allocation [85], and low-carbon economic dispatch considering carbon trading [86]. In recent years, individual carbon trading behaviors in deregulated markets have also come into people’s sight [87]. However, the current ETS still has some limits to be solved. The marginal cost of coal-fired generators is very low, and they tend not to care about the carbon emission tax, so they buy massive quotas to ensure the output [19]. This phenomenon betrays the originally established intention of ETS. Second, according to the findings, the carbon tax tends to be transferred from the upstream to the end-users through the carbon-integrated locational marginal electricity price [88]. Therefore, the generators lose incentives to develop sustainable technologies.

It is important that while emissions are created from the burning of fossil fuels at power plants, it is the actions of end-users that ultimately drive these emissions [89]. As such, it is necessary to view carbon emissions from the perspective of demand rather than simply looking at their production at power generators. To address this, a double carbon taxation mechanism has been proposed [23, 90], which would impose a tax on both the supply and consumption of carbon emissions. This approach, similar to the concept of double taxation in economics, assigns responsibility for emissions to all parties involved. For instance, many light industrial products are manufactured in developing countries but consumed in developed countries, leading to debates over who should pay for the carbon cost. The actual emissions take place in developing countries, but it is the demand of developed countries that is the root cause, and the "virtual" emissions cannot be ignored [91]. This same principle applies to the power sector, where the long chain of energy generation, transmission, and distribution can make it difficult to clearly link incentives to consumers. To address this, it is crucial to price carbon emissions from generation to end-users, providing the proper incentives across multiple sectors and allowing consumers to be charged for their responsible carbon emissions [92].

In the energy transition process, carbon market-based power system planning should be focused on. Considering the emission trading in the power system can better reveal the impact of carbon policy on power sectors, and it facilities a smooth and reliable energy transition.

2) Renewable energy certificates

In addition to limiting the output of non-renewable power plants, promoting the use of renewable energy is another way to reduce emissions. One tool that has been used to achieve this is RECs, also known as green certificates or green tags. These certificates are used to verify that a certain amount of electricity was generated using renewable energy sources. One certificate represents one megawatt-hour of renewable energy. Renewable energy generators sell these certificates, while electricity consumers are the original buyers. However, after the electricity is brought onto the grid, it becomes impossible to distinguish renewable energy from conventional energy. This means that consumers cannot choose to consume only renewable energy, but they pay extra money to support its production and take on social responsibility. The downside of this is that consumers do not receive any direct benefits from purchasing RECs, which can limit motivation to subscribe to these certificates in some countries, such as Australia. However, the research regarding renewable energy certificates is limited. In ref.[93], it is mentioned that the RECs mechanism is a kind of renewable energy support policy. In ref.[94], as a government incentive, RECs can contribute to the rapid development of renewable energy. Ref.[95] reveals the evolution of the RECs supporting scheme for promoting renewable energy in Romania. However, there is no quantitative model and analysis on how RECs benefit renewable energy plants and the overall emission. Ref.[96] points out that REC trading can relieve the government's financial burden by reducing the expenditure of subsidization of renewable energy. To verify the effectiveness of the RECs, the development of renewable energy and economic benefits under different carbon policies are investigated. Ref.[97] analyzed the tradable RECs market, where renewable energy investors receive certificates based on their production and sell RECs to retailers. The retailers are required to purchase in an amount proportional to their total sales. Ref.[98] proposed a multi-objective dynamic economic emission dispatch model for wind-solar-hydro power under tradable RECs. Considering the consumers lose motivation to purchase RECs, ref. [19] proposed a mechanism to combine RECs and ETS, which provides a mechanism for organizations to offset their emissions by purchasing certificates representing the generation of renewable energy. This helps to increase the deployment of renewable energy technologies, as organizations can meet their emissions reduction targets by purchasing RECs, rather than reducing their own emissions.

3) Energy efficiency programs

Improving energy efficiency in the residential sector has, therefore, become a critical issue for environmental sustainability. Energy efficiency technologies and practices help to reduce energy consumption and greenhouse gas emissions by reducing the amount of energy required to perform a given task. Many energy efficiency programs have been launched to encourage customers to invest on more efficient domestic appliances and promote energy conservation behaviors [99].

Demand response (DR) is an energy efficiency program that aims to manage electricity demand by incentivizing consumers to reduce their energy usage during times of high demand [100]. The goal of DR is to reduce the strain on the energy grid and prevent blackouts or brownouts caused by high demand. DR programs typically use a combination of pricing signals and direct incentives, such as rebates or credits, to encourage consumers to reduce their energy usage during times of high demand [101].

DR can be divided into two categories: incentive-based DR programs and price-based DR programs. Incentive-based DR programs offer financial incentives to end-users, who are then expected to respond to DR signals [102]. These programs can be further divided into direct load control and load curtailment. Direct load control allows the system operators to manage end-users' appliances remotely [103]., and it has been shown to be an effective tool for mitigating supply-demand imbalances in integrated power systems [104]. Load curtailment, on the other hand, only allows the system operator to cut off the end-users' supply during emergencies [105]. Ref. [106] pointed out that load curtailment is an effective control strategy against voltage instability. Although incentive-based DR can be an effective way to reduce network operation costs and address stability issues, it can also result in privacy and comfort concerns for end-users.

Compared with incentive-based DR programs, price-based DR programs are more flexible. The electricity usage profiles are stimulated by different electricity price signals, such as time-of-use (TOU) price [107], real-time price (RTP) [108], and critical peak price (CPP) [109]. The end-users schedule the controllable loads to earn maximum welfare by responding to the price signals actively [110]. In order to integrate widely spread controllable resources, different prosumers are aggregated to form collusion to earn the largest benefits [111]. Considering the different price elasticity of the customers, the individualized pricing strategy is designed for each customer to ensure the energy efficiency of the whole society [112, 113].

In the low-carbon-oriented power system planning and energy transition, the DR capability at the demand side should be fully taken into consideration since the integration of demand response and power system planning can lead to a more flexible and efficient power system and reduce the need for inefficient duplication of investments. By leveraging the flexibility of demand, the power sector can better accommodate the integration of renewable energy sources and reduce the need for fossil fuel-based generation, leading to a more sustainable and low-carbon power system.

4) Green bonds

The green bond pathway can play an important role in supporting low-carbon-oriented power system planning and energy transition. Green bonds are a type of debt instrument that can be used to raise capital for investment in environmentally friendly projects, such as renewable energy, energy efficiency, and sustainable transportation.

By providing issuers with a clear and transparent process for issuing green bonds, the green bond pathway can help attract more investment into low-carbon-oriented power system planning and energy transition projects. This can accelerate the development of renewable energy and energy efficiency technologies, reducing the reliance on fossil fuels and helping to mitigate the effects of climate change. Issuance of green bonds (GBs) is valuable for developing countries because it provides a market deepening mechanism, which enables greater liquidity for investments in the renewable energy sector.

In addition, the green bond pathway can also play an important role in increasing transparency and accountability in the financing of low-carbon-oriented power system planning and energy transition projects. This can help to build trust among investors and other stakeholders, leading to increased investment and more rapid progress towards a low-carbon, sustainable power system. Ref. [114] investigated the features of green bonds, which investors prioritize as preferential for renewable energy financing. The findings illustrated that low-interest rates, similar payback periods, economic convenience and transparency issuance are among the top preferential features for feasible green bond rollouts.

5) Distributed electricity market

Distributed electricity markets or local electricity markets are evolving rapidly, driven by the global imperative to decarbonize and democratize energy systems. With the rise of renewable energy sources and advancements in technology, we've seen a shift from centralized energy systems to more decentralized ones. This review delves into the dynamics of local electricity markets, focusing on the renewable energy market and peer-to-peer (P2P) trading.

The emerging of the local energy market allows the DERs to be traded locally within the distribution level. In the U.S., a green energy market, where distributed renewable energy and uncertain energy can be traded, is established [115]. In the Netherlands, a trading platform is established, where customers can trade self-generated energy with peers [116]. Therefore, the development of the local energy market is a promising trend. Ref. [117] proposed a bidding strategy for an autonomous smart transactive agent in the local energy market and introduced metrics and criteria for evaluating the bidding strategies. Ref. [118] proposed a systematic approach to derive the optimal bidding strategy for prosumers in a distribution-level energy market. In the local energy market, more data are generated from the prosumer side, like load profiles of EVs and ESS and energy transactions data. However, most of the data of the prosumers are not transparent, and the information is asymmetric. The conventional trading strategies are no longer suitable for the local energy market. Hence, some references further focused on the market trading behaviors in an information asymmetry context [119].

With the development of advanced Information and communication technologies, P2P energy sharing has emerged under the background of the sharing economy and is believed to be an essential technique in the next-generation energy market [120]. For example, in [14], both capacity and energy sharing between the coordinator who manages the shared ESS and the prosumers who borrow the capacity and energy from the coordinator were integrated via the proposed credit-based sharing model. In [14], the time accumulation effect has been considered via the proposed credit points, which could better reveal the essence of the sharing economy. In other words, the process of sharing is emphasized with a return of the shared capacity and shared energy. In a deregulated or regulated P2P energy-sharing market, a prosumer can share its excess energy with other prosumer in peers. Peer-to-peer energy sharing is considered an effective way to enhance the flexibility, locality, and diversity of the energy supply and demand while reducing the levelized cost of energy and carbon emission. Moreover, from the perspective of the grid, large benefits can be gained from P2P sharing in terms of reducing peak demand, lowering operation and investment costs, and enhancing system reliability and stability.

C. Regulatory Pathways

1) Renewable energy standard

Renewable energy standards require organizations to generate a minimum percentage of their energy from renewable energy sources. These standards provide a regulatory framework for the deployment of renewable energy technologies and help to increase the use of clean and sustainable energy sources. Renewable energy standards can take different forms, such as renewable portfolio standards and quotas. Renewable portfolio standards require a certain percentage of electricity generated by a utility or state to come from renewable sources and are commonly used in the United States. Quotas are similar to renewable portfolio standards but specify an absolute amount of renewable energy that must be generated rather than a percentage of total energy production.

However, it is important to note that the design and implementation of renewable energy sources can have a significant impact on their effectiveness. For example, weak renewable sources that set low targets or provide insufficient financial incentives are unlikely to drive significant renewable energy deployment. Effective renewable energy sources should be designed to support the development of renewable energy technologies at all stages, from research and development to commercial deployment.

2) Energy efficiency standard

Energy efficiency standards are policies that set minimum performance requirements for energy-using products, buildings, and industrial processes, with the goal of reducing energy consumption and greenhouse gas emissions. Energy efficiency standards require organizations to adopt energy efficiency technologies and practices. Energy efficiency standards also have different forms. For example, building energy codes: These set minimum energy performance requirements for new and renovated buildings and can include requirements for insulation, heating and cooling systems, and lighting. Appliance and equipment standards are another type of form. These set minimum energy efficiency requirements for products such as refrigerators, air conditioners, and lighting fixtures. On the other hand, industrial energy efficiency standards set energy efficiency requirements for specific industrial processes, such as refining or chemical production.

Energy efficiency standards can have a significant impact on reducing energy consumption and emissions as they drive the production and use of more energy-efficient products and technologies. They can also help to create a market for energy-efficient products and services, which can drive innovation and cost reductions.

However, it is important to note that energy efficiency standards need to be regularly updated to reflect technological advancements and changes in energy consumption patterns. They also need to be effectively implemented and enforced to ensure that they have the desired impact.

3) Net metering

Net metering provides a regulatory framework for the integration of renewable energy sources into existing power systems [121]. Under a net metering arrangement, the customer's meter measures the difference between the electricity they consume from the grid and the electricity they generate and feed back into the grid. Any excess electricity is credited to their account, and they can use these credits to offset their future electricity consumption. Net metering can play a critical role in promoting the deployment of small-scale renewable power systems, such as rooftop solar panels. Allowing customers to offset their electricity consumption with their own generation can reduce their electricity bills and provide a financial incentive for renewable energy deployment.

However, it is important to note that the design and implementation of net metering policies can have a significant impact on their effectiveness. For example, policies that set low limits on the size of the renewable power systems that can participate or that pay low rates for excess electricity may not provide sufficient incentives for renewable energy deployment.

4) Feed-in tariff (FIT)

Feed-in tariffs, on the other hand, provide financial incentives for renewable energy generation by guaranteeing a fixed price for the electricity generated[122]. Under a FIT program, renewable energy generators receive a set price per unit of electricity generated. This provides a financial incentive for renewable energy deployment, as it allows the generator to earn a profit from their investment [123].

However, it is important to note that the design and implementation of FITs can have a significant impact on their effectiveness. For example, FITs that set low prices or provide insufficient financial incentives are unlikely to drive significant renewable energy deployment [124]. Effective FITs should be designed to support the development of renewable energy technologies at all stages, from research and development to commercial deployment [122]. Considering the benefits of the prosumers under a FIT scheme are relatively marginal, some types of new market structures emerge, such as the local energy market at the community level [117], the energy sharing market [15], the peer-to-peer trading market [125], etc. These market structures can be further classified as community-based markets (an operator is required), decentralized markets (no operator), and composite markets [120]. The emergence of these local energy markets allows the DERs to be traded locally within the distribution level [126]. Participating in these markets can earn higher benefits for the prosumers with DGs. In the U.S., a green energy market, where distributed renewable energy and uncertain energy can be traded, is established [115]. In the Netherlands, a trading platform is established where customers can trade self-generated energy with peers [116]. Therefore, the development of LEM is a promising trend.

V. Mathematical modeling techniques

A. Low-carbon-oriented Power System Modeling

Power system planning has received a lot of attention in the academic community. Optimal network expansion has always been one of the most important issues in power system planning, referring to a comprehensive analysis to determine the time, location, and type of adding new facilities to facilitate economic, secure and reliable operations of power systems. In terms of the mathematical models used, the research can be divided into two categories: static and dynamic. In the static model, the planning of new transmission lines and generators is based on the expected electricity demand at the end of the planning period. On the other hand, the dynamic model takes into account changes in electrical power demand and the evolution of the electrical system over time, making it a more flexible approach. Thus, more factors can be taken into account, such as annual load growth, inflation rate, environmental changes, policy, etc. The goal of planning is to minimize the total cost of the electrical system, including the cost of constructing new infrastructure and operating the system. To achieve this, various algorithms and techniques, such as linear programming and heuristic methods, have been proposed to solve the optimization problem. The choice of method depends on the specific requirements of the planning problem. Overall, planning is a crucial aspect of electrical engineering as it helps to ensure the reliability and efficiency of the electrical system.

Different from conventional power system planning, low-carbon-oriented power system planning requires further consideration of the process of designing and developing a power system that prioritizes the use of low-carbon sources of energy and minimizes greenhouse gas emissions. The goal of low-carbon power system planning is to transition towards a more sustainable and environmentally friendly energy mix. Therefore, in the mathematical models, it should further take carbon constraints or carbon trading into account. Some references consider the retirement of coal-fired power plants (CFPPs) in the planning problem. In [127], a rigorous mathematical model was presented considering generation expansion and retirement planning. The stochastic programming considered the random outage of the generators, and the simulation results found that the retirement option was beneficial to the power system's reliability. In [128], the retirement of the aging generators and the rehabilitation problem were mathematically formulated. It pointed out that rehabilitation can also be an economical option. In [129], a mathematical model aiming at electricity network expansion and CFPPs retirement targeting low-carbon energy transition was presented. The mathematical model considered carbon tax and carbon trading of thermal generators as environmental factors. In [130], the early retirement of CFPPs was focused in the context of the renewable energy transition and an energy transition roadmap was proposed based on average carbon reduction cost. Table I provides a classification of existing publications.

1) *Renewable Energy Integrated Planning*

In the effort to combat climate change, renewable energy is seen as a crucial component in the transition to a more sustainable energy mix. Carbon-oriented power system planning must, therefore, focus on integrating renewable energy sources effectively. As mentioned previously, the uncertainties associated with renewable energy are a major challenge in power system planning, particularly in the area of low-carbon-oriented planning. In this section, a thorough and in-depth review of planning for the integration of renewable energy will be provided.

TABLE I
CLASSIFICATION OF EXISTING PUBLICATIONS RELATED TO POWER SYSTEM PLANNING

No.Ref	Static	Dynamic	Deterministic	Probabilistic				ESS planning	CFPP retirement	Carbon target
				Renewable energy	Load	Market	Other Events			
[131]	☑				☑					
[132]	☑		☑							
[133]	☑		☑							
[134]	☑				☑		☑			
[135]		☑								
[136]		☑			☑	☑				
[137]		☑			☑					
[138]	☑				☑		☑			
[139]		☑	☑							
[140]		☑	☑							
[141]		☑	☑							
[142]	☑			☑						
[143]	☑			☑	☑					
[144]		☑		☑			☑	☑		
[145]	☑			☑	☑					☑
[146]		☑		☑	☑	☑	☑			
[147]		☑		☑						☑
[148]		☑		☑	☑				☑	☑
[149]		☑		☑	☑			☑		☑
[150]		☑		☑	☑				☑	☑
[130]		☑	☑					☑	☑	☑
[151]		☑	☑					☑	☑	☑

The increased use of renewable energy sources will make the power system more complex. The variability inherent in renewable energy sources results in a deviation between energy generation forecasts and actual energy output, which makes it challenging to maintain a balance between supply and demand in real-time with limited storage and backup capacity [152]. To address this issue, it is becoming increasingly important to integrate flexible energy technologies to enhance the flexibility of the power system. The traditional power system planning problem must be adapted to incorporate the integration of renewable energy, which involves changes to the objective functions, constraints, and uncertainty analysis [153].

In the objective function, it is important to not only consider the investment cost but also the environmental cost [154]. As renewable energy sources are expected to play a larger role in power generation, the corresponding objective function must also be updated. The most common approach is to maximize the share of renewable energy in the power generation portfolio, such as maximizing the share of renewable energy in power generation [155] or maximizing the contribution of renewable energy to peak load [156]. Some studies also focus on minimizing excess wind and solar power [157], minimizing the backup generation and transmission capacity, and minimizing the additional reliability requirements of variable renewable energy. As a result, the single objective function may be expanded to a multi-objective function, which takes into account investment cost, environmental impact, and system reliability.

In addition to the conventional power balance, capacity expansion, generation and transmission, and fuel supply constraints found in traditional power system planning, the constraints in renewable energy integrated planning may also include policy constraints, particularly regarding carbon policy [158]. The carbon emissions from thermal power generators may be limited by government-mandated emission reduction targets. Additionally, some countries have set a goal for the integration of renewable energy, often in the form of a renewable power rate constraint, as part of their strategy to address climate change and energy [159].

The uncertainty analysis in the context of low-carbon-orientated planning has been discussed in the literature. Two commonly used methods, stochastic optimization and robust optimization, have been proposed [160]. Stochastic optimization involves using representative scenarios with specific probabilities to address the uncertainties in renewable energy integrated planning. While this approach can improve the planning solution, it can also reduce computational efficiency, especially when the number of scenarios is large. To overcome this, advanced scenario generation technologies are necessary to effectively select and reduce the number of representative scenarios. On the other hand, robust optimization deals with uncertainties by using parametric bounds. The robust optimization approach provides planning solutions that remain optimal even in the worst-case scenario, but the plans may be overly conservative. In recent years, with the advancement of machine learning and deep learning technologies, more sophisticated tools have been employed to model the uncertainties of renewable energy. For instance, some studies have proposed using machine learning for solar power generation prediction (e.g., [161]), using Bayesian neural networks for behind-the-meter PV generation estimation (e.g., [162]), and using nonparametric Bayesian methods based on the Dirichlet process mixture model to estimate the distribution of wind farm generation (e.g., [163]). These data-driven methods can be used to improve the accuracy of the uncertainty model in renewable energy integrated planning.

2) Energy Storage Planning

Energy storage planning, including BESS planning, is a crucial new technology that can regulate the output of renewable energy sources in the electricity network. The planning of BESS location and size is a significant part of low-carbon-oriented power system planning. However, there is a need to explore how to effectively integrate BESS into the power system. The overall objective function of the BESS planning is also minimizing the total cost, which includes the cost of constructing new infrastructure, battery degradation cost, operating the system, and mitigating environmental impact. In the constraints, besides the network's physical constraints, the BESS system should also meet the energy demand and operate within the capacity and SOC constraints. In some problems, the mathematical formulation should also consider the BESS's participation in the electricity market, such as arbitrage behaviors and providing ancillary services. In refined modeling, the complex lifetime and efficiency function require modeling. In comparison to traditional technologies used in generation expansion planning (GEP), the lifespan of Energy Storage Systems (ESS), such as batteries, is significantly impacted by the numerous cycles they undergo, and their efficiency is dependent on various complex factors, resulting in highly nonlinear models. Despite the importance of modeling the lifespan in terms of cycling and the efficiency of BESS, this area of research is limited. However, it is crucial to accurately model these factors to avoid underestimating the costs associated with BESS.

Ref. [164] focused on the net present value (NPV) of saving and optimizing the capacity of the battery. Ref. [165] not only solved the sizing of the batteries at all the electricity nodes in the distribution system but also considered the voltage regulation and peak load shifting in the cost-benefit function. Besides, the aging of the batteries is considered as a cost that is linear to the discharging circle. Ref. [166] chose the total cost of the system as the objective function to solve the planning of siting, sizing, and rated power of the batteries. Ref. [167] proposed a planning and control strategy for BESS where the maximum profit can be reached by providing the primary frequency regulation service. Ref. [168] utilized game theory to solve the planning of a hybrid power system comprised of wind turbines, PVs, and batteries. With more and more DERs emerging in the distribution system, the uncertainties cannot be neglected. In [169], the Monte Carlo method and stochastic scenario method were synthetically applied to realize the stochastic planning of energy storage systems. In [170], an energy storage planning model considering the chance-constrained optimization with non-parametric probability functions has been proposed, which eliminated the dependency of uncertainty factors on statistics and modeled the probability distribution of irregular shapes. Because of the uncertainties in the system, the security and stability of the power grid have been challenged. Ref. [171] focused on the location planning of centralized energy storage and distributed energy storage from the perspective of grid stability. In [172], a two-stage stochastic optimization model was proposed to solve the planning of the BESS, and a load-shedding strategy was considered to improve the stability of the system. In [173], a hierarchically optimal allocation of battery energy storage system was proposed, where the sitting of the BESS was solved based on voltage violation risk in the first stage, and the sizing was solved in the second stage.

Apart from BESS planning, the ESS's diversity needs to be addressed, including fixed or mobile, centralized or distributed, etc. The portfolio of different types of ESS to enhance the network flexibility and economy is promising future work.

3) Integrated Network Planning

An integrated energy network, also known as a multi-energy network, is a strategy for finding environmentally responsible and cost-effective solutions that balance energy supply and demand [174]. It aims to support long-term sustainability by incorporating cutting-edge energy conversion technologies like power-to-gas (P2G). The multi-energy network primarily encompasses electricity networks, gas networks (natural gas or hydrogen), and heat networks. The energy infrastructure in this system is responsible for producing, transforming, and transporting energy and includes network facilities (electricity feeders, gas pipelines, and heat networks), energy conversion units (such as boilers, gas power plants, P2Gs, heat pumps, and cogeneration plants), and energy storage devices (such as batteries, gas tanks, heat tanks, and chemical storage). In terms of network modeling, different types of networks share some similarities and differences [175]. The driving force behind electricity network modeling is voltage gaps, whereas thermal and gas networks are based on pressure gaps. These differences in driving forces lead to variations in modeling, with electricity networks modeled using nonlinear power flow and simplified by linearized technologies [176]. Gas network modeling is based on nonlinear compressible flow, while thermal network modeling is based on conservation equations. A linearization approximation method has been proposed to simplify gas flow modeling in ref. [177]. The summary of the modeling structure, conversion mode, and storage devices in the literature is presented in Table II.

4) Coordinated Planning with the Transportation Network

The increasing use of EVs has created a connection between electricity networks and transportation networks. This coupling relationship is typically established at the charging points for EVs, as depicted in Fig. 3. This is because the charging of EVs is a significant demand on electricity networks, and charging points are placed within transportation networks to take advantage of traffic patterns.

In a modern, advanced smart grid, the multi-networks will not only involve the single connection described above but may also involve multiple connections. For instance, when thinking about the efficient scheduling and management of EV charging, the relationship between the information network, electricity network, and transportation network must be considered, as illustrated in Fig. 4. In this framework, both the traffic situation and the electricity network will be monitored. Based on this monitoring, the charging platform will offer drivers appropriate charging schedules that satisfy their charging needs while minimizing traffic congestion and wait times and reducing the load on the electricity network.

TABLE II
CLASSIFICATION OF EXISTING PUBLICATIONS RELATED TO INTEGRATED POWER SYSTEMS

Ref.	Structure			Energy conversion mode			Storage			
	CHP	CCHP	P2G	to electricity	to heat	to gas	BESS	TES	HES	NGS
[178]	☑			☑	☑		☑	☑		
[179]	☑			☑				☑		
[180]	☑			☑	☑		☑			
[181]	☑			☑	☑		☑	☑		
[182]	☑			☑	☑					
[183]		☑		☑	☑		☑	☑		
[184]		☑			☑					
[185]		☑	☑	☑	☑					☑
[186]		☑		☑	☑		☑	☑		
[187]		☑		☑	☑			☑		
[188]			☑	☑		☑		☑	☑	☑
[189]			☑	☑	☑	☑	☑		☑	
[190]	☑			☑	☑	☑	☑	☑	☑	

To this end, it can be concluded that the transition and planning of future smart grids is a multi-network science. As a result, current references aim to model and examine these interconnections and establish coordination between the multiple networks.

In the literature, the collaborative planning models of EV FCSs, transportation systems, and distribution systems were well studied. The EV FCSs are expected to capture the largest traffic flows in the transportation network [191]. The electricity network is planned to support the physical connection between the FCSs and the electricity network [192]. Thus, FCSs become coupling points between the electricity and transportation networks, and the two types of networks become intensely correlated [75].

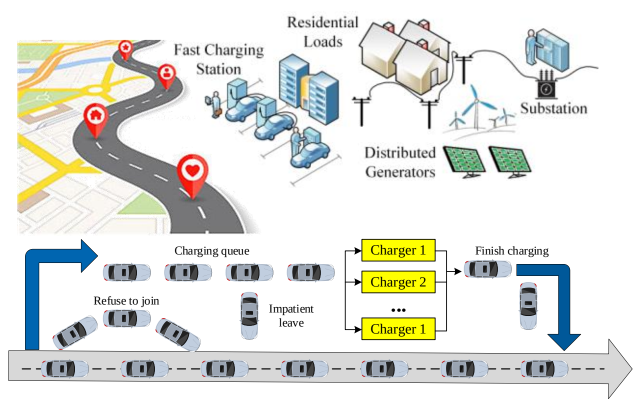

Fig. 3. System structure of coupled electricity and transportation networks.

After properly modeling the coupling relationship between the electricity network and the transportation network, the sitting and sizing problem of the charging stations should be solved through the optimization problem [191]. The related mathematical model includes the charging model, the probabilistic modeling of the arrival time and charging demand, the battery degradation of EVs, etc. [193]. To ensure the quality of the charging service, the queueing model is applied to estimate the waiting time [194]. In the energy transition process, the number of EVs will increase dramatically to take the place of conventional gasoline vehicles. Therefore, the planning model should fully consider if sufficient charging facilities are invested [195]. Furthermore, the reliability and risk model will be utilized to assess the impact of EV penetration on the electricity network [80]. In the context of low-carbon-oriented power system planning, FCS planning is an important aspect to consider. The goal is to integrate clean energy sources and reduce the carbon footprint of the transportation sector. For example, the FCS can be powered by renewable energy resources.

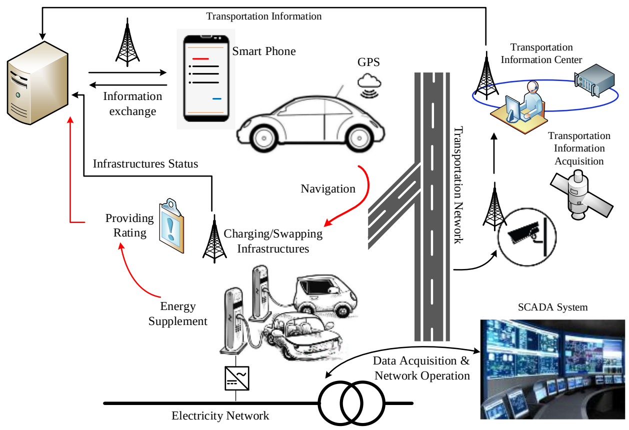

Fig. 4. Structure of smart charging scheduling system for EVs.

B. *AI-assisted solutions*

1) *Machine-learning-assisted computation method*

The data-driven methods have been given extensive attention in recent years and applied to tasks in different fields. One merit of the data-driven methods is that they are spurred on by real data rather than being driven by mere intuition or personal experience. Thus, they are more practical with fewer assumptions or simplified models involved, which motivates us to employ them hereby for dealing with the planning problem.

The traditional method of optimization based on models requires information about the mathematical models and parameters of a system. However, some of these parameters may not be readily available in real-world scenarios [196]. To address this issue, data-driven approaches can be used to help make decisions in the operation of the smart grid by analyzing power flow, calculating gas flow, and modeling thermodynamic behavior, among others [197]. These conventional models have nonlinear characteristics, making it challenging to optimize their behavior [198]. For instance, in data science, the steady state of a power system can be seen as a high-dimensional vector in a hyperspace, while the nonlinear AC power flow models describe a nonlinear hyperplane that the vector lies on. The goal of machine learning methods is to identify the relationship between decision variables and relevant state variables. For example, the relationship between power injection at each bus and power flow and voltage can be determined through regression analysis for power flow analysis [10]. Similarly, the relationship between the power of thermostatically controlled loads and indoor temperature can be determined through regression analysis for thermodynamic behavior modeling. These processes do not require knowledge of system parameters.

A data-driven approach is used to address the stochastic optimization issue in power system planning. Machine learning tools, such as convolutional neural networks (CNN), are utilized to capture the nonlinear features of the system's steady states [151]. These neural networks are trained using historical and generated data without relying on prior knowledge of the system parameters, making it possible to solve the problem of unknown parameters in mathematical models. This learning-based method has a higher level of accuracy compared to the traditional model-based approach. Additionally, the use of data-driven methods in optimization reduces the computing time, as it replaces the calculation of massive state variables, power flow constraints, voltage constraints, and other nonlinear constraints.

In real-world applications, data sets can often be incomplete due to various reasons, such as sampling errors and communication delays. These missing data can have a negative impact on the accuracy of the trained model. To address this issue, a generative adversarial network (GAN) can be used to deal with the common problem of missing data in practical applications [199]. Compared to other supervised learning algorithms, such as CNN, long short-term memory (LSTM), and Bayes linear regression, GAN can reduce the impact of missing data on accuracy. Thus, the use of the modified GAN improves the feasibility of the proposed learning and optimization integrated method in practical applications.

Based on the learning result, a hybrid learning and optimization framework can be put forward. Based on data-driven power system analysis and future network condition prediction, a low-carbon-oriented power system planning strategy is designed. This part of the work creates a new research paradigm to utilize machine-learning technologies in the power system planning problem. The learning-based algorithms bring new perspectives in addressing complex system problems effectively and efficiently. The theoretical models will guide a trustworthy design of the low-carbon energy transition. Cost savings can be realized in the energy transition of the power systems associated with more accurate and efficient modeling. The optimal transition pathways identified for integrated energy networks will reduce the need for inefficient duplication of investments. Progressing world-class science in energy economics and complex system modeling theories will boost the nation's recognized and emerging intellectual leadership in energy sustainability.

2) *Bayesian-based learning to model the uncertainties*

The uncertainties are critical problems that will affect the planning results in low-carbon-oriented power system planning, and the uncertainty level has been increasing in recent years. As mentioned, scenario-based stochastic optimization and robust optimization are applied to deal with uncertainties. However, conventional methods have their limits. The first one is computationally inefficient, and the latter one can be over-conservative.

Bayesian-based learning is a type of machine learning that incorporates Bayesian probability theory to model uncertainty in predictions. In Bayesian-based learning, Bayesian learning uses Bayes' theorem to determine the conditional probability of a hypothesis given some evidence or observations, allowing for more nuanced and informed predictions. This approach provides a way to incorporate prior knowledge, capture uncertainty in model parameters, and update beliefs based on new data.

One popular example of Bayesian-based learning is Bayesian linear regression, where the parameters of the model are treated as random variables with prior distributions. These prior distributions are updated as new data is collected, resulting in posterior distributions that represent the updated beliefs about the parameters.

Another example is Bayesian neural networks, where the weights of the network are treated as random variables with prior distributions. This allows for capturing uncertainty in the model predictions, as well as providing a way to regularize the model and prevent overfitting.

The nonparametric Bayesian framework based on the Dirichlet process mixture model (DPMM) and variational Bayesian inference is a useful tool for dealing with uncertainties in power systems. The DPMM is a flexible, nonparametric model that allows for the estimation of parameters of underlying distributions in a data set. The variational Bayesian inference is a scalable approximation method that can be used to perform Bayesian inference in complex models, such as the DPMM. Then, based on DPMM, a dynamic data-driven probabilistic optimal power flow algorithm can be developed when solving the planning problem [200].

Additionally, Bayesian-based learning can be incorporated into robust optimization. The DPMM can be used to create a data-driven approach for defining the uncertainty set. A study has proposed a data-driven adaptive nested robust optimization approach that combines the DPMM with adaptive robust optimization through a four-level optimization framework [177]. This data-driven approach accounts for the correlation, asymmetry, and multi-modal nature of uncertainty data, resulting in less conservative solutions. The proposed framework is also robust to both variations in parameters and anomalous measurements.

3) Deep-reinforcement learning (DRL)-based method to model the behaviors of market entities

The DR-based power system planning is critical to the future energy transition [201]. In other words, the low-carbon-oriented power system should further consider the individual response to the planning scheme to avoid over-investment [202]. To this end, a refined and efficient model should be developed. However, there are some challenges in modeling individuals. Firstly, the conventional model-based method relies on having knowledge of information about market participants, but many parameters are not shared due to privacy concerns, leading to asymmetric information. Secondly, to overcome the nonlinear issue in conventional optimization-based methods, the physical non-convex operating characteristics of prosumers are often ignored in the literature, but this assumption may not be realistic. Thirdly, conventional model-based methods use stochastic modeling techniques, but it is challenging to model randomness accurately. Fourthly, the conventional methods heavily rely on the optimization process, which is often time-consuming, especially when the number of decision variables is large. As a result, these conventional methods may struggle to rapidly adapt to changing conditions.

Therefore, DRL methods can be applied to address the above challenges properly [119, 203, 204]. DRL is a subfield of machine learning that combines deep learning and reinforcement learning. Reinforcement learning is a type of machine learning that focuses on training agents to make decisions in an environment by maximizing a reward signal [205]. In DRL, deep neural networks are used to approximate the value function or policy of an agent. The agent interacts with the environment by taking actions and receiving rewards, and the neural networks are updated based on the observed outcomes. The combination of deep learning and reinforcement learning allows DRL to handle high-dimensional state spaces and complex decision-making problems [206].

After analyzing the microscopic behaviors of individuals, the result can be aggregated into a macro-level model, which can be integrated into a low-carbon planning model [195]. The aggregated macro-level model can present the sensitivity of electricity demand to the planning schemes. This strategy can be flexibly adapted to the planning model. With the application of DRL, the influence of the power system planning schemes on the electricity usage patterns of end-users can be considered in the planning model.

4) Comparative analysis

While all AI-assisted methods offer robust tools for tackling the challenges of low-carbon-oriented power system planning, their suitability varies based on the specific problem at hand. Machine-learning-assisted computation is versatile and can be used where large datasets are available. Bayesian-based learning is best when uncertainties are dominant, and a probabilistic perspective is necessary. Lastly, DRL shines in complex decision-making scenarios where understanding behaviors and interactions is crucial.

For a comprehensive decision, considering the specific requirements of a task and understanding the nature of the data and environment is vital. All methods, however, underline the growing importance and potential of AI-assisted solutions in reshaping the future of power system planning and the broader energy sector.

A comparative analysis is shown in Table.

TABLE III
COMPARATIVE ANALYSIS ON DIFFERENT AI-ASSISTED METHODS.

Methods	**Machine-learning-assisted computation Model**	**Bayesian-based Prediction**	**DRL-based Method**
Focus	Data-driven optimization	Modeling uncertainties	Modeling behaviors of market entities
Core Technique	Neural networks (e.g., CNN, GAN)	Bayesian non-parametric probability, Bayesian linear regression, DPMM	Reinforcement learning (DQN, DDPG, etc)
Main Application	- with abundant historical and generated data - with complex input-output relationships	- Systems with significant uncertainties. - Problems needing a probabilistic understanding	- Behavioral analysis & demand response - Dynamic decision-making with changing conditions
Benefits	- Reduced assumptions - Handles complexity, non-linearities	- Informed predictions - Incorporates prior knowledge & uncertainty	- Handles high-dimensional spaces - Adapts to changing conditions

	- Reduced computing time	- Regularization and overfitting prevention - Handling complex distributions - Continually updated with new data	- Integrates micro and macro behaviors - Addresses asymmetric information & privacy
Challenges	- Requires large datasets for high accuracy - Can suffer from missing or incomplete data	- Computationally intensive for large datasets - Complex model inferences - Requires a prior which might be subjective	- Requires a well-defined reward mechanism - Computationally more intensive than others - Needs substantial interaction with the environment

VI. Discussion on Future Roadmap

The transition towards a low-carbon energy system is an imperative, not just from an environmental standpoint, but also considering socio-economic and political ramifications. As delineated in this paper, the path to this transition is rife with complexities. Here, we set forth a cohesive roadmap to guide future endeavors in this direction.

1) Holistic Integration:

Transitioning to a low-carbon energy system is not merely about adding renewable energy sources to the grid. It's about a holistic integration where renewable and non-renewable sources, storage solutions, and demand-response mechanisms work in harmony. The grid of the future must be intelligent, resilient, and adaptive.

2) Technological Advancements:

While renewable technologies have come a long way, continuous research and development (R&D) is paramount. Efforts should focus on increasing the efficiency of renewable sources, advancing energy storage solutions, and enhancing grid connectivity to handle intermittent renewable supply.

3) Socio-economic Considerations:

It’s essential to recognize that the transition will have socioeconomic impacts, including possible disruptions in employment in traditional energy sectors. Planning must involve skilling programs, community engagement, and frameworks to ensure that the transition is just and inclusive.

4) Policy and Regulatory Support:

A shift of this magnitude requires robust policy and regulatory backing. This would mean providing incentives for renewable energy adoption, crafting supportive tariffs and pricing mechanisms, and setting clear standards and guidelines for grid integration.

5) AI and Advanced Modeling:

Traditional models might fall short in predicting the complex dynamics of a largely renewable grid. Implementing machine learning and AI can provide accurate predictions, optimize grid operations, and aid in demand forecasting. This paper's emphasis on advanced machine learning-assisted solutions is particularly timely given the data-rich environment of modern power systems.

6) Market Mechanisms:

The future energy market must be flexible, allowing for peer-to-peer energy trading, dynamic pricing, and integration of decentralized energy sources. Platforms should be developed where prosumers can actively participate, trade, and benefit from the energy transition.

7) International Collaboration:

Climate change is a global challenge, and so is the energy transition. Collaboration at an international level can facilitate the sharing of best practices, joint R&D ventures, and the crafting of inter-country energy trade policies.

8) Continuous Review and Feedback:

Given the dynamic nature of technology, markets, and consumer behavior, it's essential to have mechanisms in place for continuous review. Regular feedback loops, stakeholder consultations, and performance evaluations should be integral components of the planning process.

9) Resilience and Security:

With increased digitalization and connectivity, the future grid must be resilient not just to physical disturbances but also to cyber threats. Investment in cybersecurity measures, regular audits, and establishing protocols for threat detection and response are crucial.

VII. Concluding remarks

In conclusion, the challenges and pathways associated with low-carbon-oriented energy transition and power system planning are complex and diverse. This paper offers a review of the drivers, obstacles, pathways, and modeling technologies related to low-carbon power system planning and energy transition. The energy sector is confronted with the challenge of balancing increased energy access, security, and affordability while simultaneously reducing greenhouse gas emissions. Overcoming these challenges necessitates a comprehensive, integrated, and multi-stakeholder approach.

The creation of low-carbon energy transition roadmaps and power system planning strategies can provide a framework to guide this shift toward a more sustainable future. These strategies should account for the unique circumstances and resources of each country and region, considering a wide array of factors, such as technological innovations, market trends, and social and political considerations. Ultimately, the success of the energy transition hinges on the collaborative efforts of governments, industry, and civil society working together to achieve a common objective: a low-carbon energy future.

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