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REVIEW ARTICLE-ELECTRICAL ENGINEERING

# Emerging Trends and Approaches for Designing Net-Zero Low-Carbon Integrated Energy Networks: A Review of Current Practices

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## Abstract

The incorporation of net-zero technology into preexisting energy networks is crucial for facilitating the shift toward an ecologically conscious and sustainable energy infrastructure. The primary objective of this integration is to effectively decrease carbon footprints and to provide a comprehensive understanding of the current approaches and trends related to the design and management frameworks of integrated energy networks. The initial section of this study establishes the foundation for a comprehensive examination of the particular challenges associated with decarbonization in the strategic and operational aspects of integrated energy networks. The subsequent analysis proceeds to elucidate the fundamental framework and technological architecture upon which these energy networks are constructed. This provides significant insights into the operational complexity and efficacy of the system. In addition, the paper provides a concise examination of prominent frameworks and alternative approaches that tackle the issue of low-carbon design and administration. The degree of accuracy facilitates individuals when selecting systems that align with the specific requirements of unique circumstances. Furthermore, this study provides explicit suggestions for future research based on an examination of the distinct attributes and framework of integrated energy networks. The anticipated outcome of implementing these recommendations is to enable the advancement of sustainable development and expedite the shift toward energy infrastructure with reduced carbon emissions. This will make a significant contribution to the collaborative endeavor of mitigating climate change and fostering a sustainable energy future. This study further elucidates the significant contribution of integrated energy networks in addressing climate change and enhancing energy efficiency. It achieves this by synthesizing a complete range of concepts sourced from many academic papers, industry reports, and case studies. This statement offers an examination of the multifaceted technological, legislative, and planning factors that contribute to the attainment of net-zero objectives.

**Keywords** Integrated energy networks · Green technologies · Decarbonization · Low emission energy networks · Energy forecasting

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## 1 Introduction

The extensive reliance on fossil fuels has resulted in various problems, such as environmental pollution, the emission of greenhouse gases, and inefficiencies in energy production [1, 2]. The methods employed by a society to harness and utilize energy significantly influence its economic growth, geographical layout, and international relations [3, 4]. Major shifts in the global electricity sources have historically been driven by significant changes in society and geography. For instance, the transition from firewood and water power to hydrocarbons during the late 1800s, and later, from fossil fuels to petroleum in the 1900s, has brought about substantial transformations [5, 6]. The current challenge in the power sector is to usher in a new era of energy production and consumption characterized by efficiency, the use of low-carbon energy sources, and global accessibility to these resources [7, 8]. The impact of climate change-related problems and the severity of extreme weather events play a crucial role in shaping both energy production and demand. To address these challenges, policies focusing on conservation, promoting the economics of renewable energy adoption, and implementing energy-saving technologies are now widely acknowledged as the most feasible path toward achieving low-carbon energy network expansion within the energy industry [9–11].

Several advanced countries and regions, including the United States (USA) and the European Union (EU), have taken significant strides in implementing carbon policies and committing to achieving net-zero carbon emissions by the year 2050, as part of a global movement toward low-carbon transformation. China, too, has made substantial pledges in this regard, aiming to strengthen its regional commitments to achieve a “carbon peak” by 2030 and attain “carbon neutrality” by 2060 [12]. This commitment was made public in September 2020 and has spurred the development of integrated energy networks (IENs) as a means to achieve the goal of net-zero carbon footprints. IENs encompass the integration of diverse energy sources, innovations, and facilities with the aim of optimizing the production, storage, distribution, and utilization of energy. The primary objective of these networks is to optimize the performance, dependability, and ecological viability of energy systems through the integration of diverse energy carriers, including electricity, natural gas, heat, and even transportation fuels.

Notably, various economic IEN development initiatives have been launched worldwide, such as the EU ELEKTRA, Baiye Smart City, Sino-Singapore Tianjin Ecological City, and Shanghai Chongming, which serve as examples highlighting the significance of IENs in the process of decarbonization [13, 14]. These initiatives demonstrate the growing recognition of IENs’ potential to play a crucial role in achieving carbon reduction targets and promoting sustainability on a global scale. Moreover, the significance of enacting zero-carbon laws and the dynamic involvement of IENs within energy networks have surfaced as encouraging alternatives to accomplish the goal of zero-carbon emissions.

As reported in references [15, 16], a substantial 79% of global greenhouse gas emissions (GHGE) are attributed to electric power and various sectors, including transportation, along with land-use changes. To address this challenge, the European National Assembly took significant steps by adopting the clean energy for all Europeans package in 2018. This legislative initiative aims to kick-start the necessary power transformation to provide European citizens with reliable, affordable, and eco-friendly energy sources [17–21]. In the pursuit of reducing carbon footprints, Cheng et al. [22] conducted an investigation using a nexus approach that integrated various ecological domains like water and electricity. This approach seeks solutions for institutions to decrease their carbon impact. Furthermore, embracing digitalization through the deployment of innovative information and communication technologies (ICT) like internet of things (IoT), which includes prevalent and multi-functional signaling, enables proactive management and potential productivity gains in embedded facility planning [23].

Smart energy networks offer a promising avenue for reducing GHGE by optimizing power reserves to meet practical demands and respond to grid signals. The features and underlying theoretical and practical models of smart energy have been extensively explored in references [24–27]. Several institutions have already observed a decline in carbon emissions by implementing smart energy monitoring and sustainable energy practices. To achieve efficient transitions to smart energy networks, it becomes crucial to integrate multiple energy sources, renewable energy options, and decentralized energy networks into the intelligent sector, ultimately benefiting customers [28–31]. Despite the potential advantages, the full implications and intricacies of adopting IENs remain unclear, which poses challenges to their widespread adoption [32–36]. It is essential to address the energy trilemma, which involves balancing electricity prices, energy security, and carbon emissions, as well as the energy quadrilemma, which encompasses maintaining a stable energy market, before making any significant transitions in energy systems [37].

### 1.1 Examining the Way to Zero-Carbon Future

The profound importance of the low-carbon transition trajectory is readily apparent in its impact on the structure of forthcoming energy frameworks [38–41]. Through a comprehensive analysis of highly cited scholarly articles on the subject of low-carbon evolution routes within our chosen corpus of literature from the IENs, it is evident that researchers have focused their efforts on developing transition routes that are responsive to various time and location parameters, as well as the constraints posed by these phases of transition [42–46]. Figure 1 depicts a grouping scheme that categorizes the primary factors examined in research pertaining to trajectories of low-carbon transition. Research efforts investigating the development of low-carbon energy systems have examined various geographical and temporal scales, including urban, national, regional bloc, and global levels. These investigations have been accompanied by short, medium, and long-range projections. Scholars have conducted research on the many limits that impact the development of route formulations in the field of energy [47]. These limitations may be categorized into two main types: internal limitations and extrinsic limitations. The internal restrictions of the focal energy structure include energy classifications [48], carbon emissions [49], and energy requisites [50]. On the other hand, the exterior limitations consist of economic development, governmental directives, and community engagement [51, 52].

A more comprehensive strategy to designing energy system low-carbon transition paths is needed to achieve balance among varied decarbonization goals. Simulation models' transition scenarios, such as complete renewable energy, are difficult to achieve in the near future, creating dissonance [37]. Model correctness in energy system low-carbon transition paths has to be scrutinized [38]. Scholarly work also shows that low-carbon transition paths' uncertainty might cause economic and environmental vulnerabilities [39], energy disparity [43], and energy poverty [44]. Scholars recommend energy legislation and regulations, stakeholder accountability, and cross-sectoral coordination to mitigate transition-related risks [45, 46]. For robust transition paths, much study is needed.

## 1.2 Investigating the Dissemination of Zero-Carbon Innovations

The crucial advancement of energy systems toward zero-carbon states relies significantly on the adoption and propagation of zero-carbon technological advancements [53–55]. Across various domains, multiple attempts and approaches have emerged, all aimed at achieving net-zero goals [56–58]. After an examination of extensively referenced papers within our selected literature pool from the IENs, pertaining to the dissemination of zero-carbon technologies, it becomes evident that researchers have predominantly directed their attention toward renewable energy innovations, pollution mitigation technologies, and other technological enablers that expedite the progression toward sustainable energy paradigms.

Figure 2 shows technologies that have been prominent in our writing. Researchers have focused on power generation and storage for renewable energy. Solar and wind power are the most well-studied and potential renewable energy sources [59, 60]. Hydrogen and battery storage have become essential for renewable energy integration. Carbon capture solutions and environmentally friendly production technologies (e.g., combined heat and power systems [61] and eco-friendly desalination techniques) have been examined for pollution management. Academic research emphasizes the importance of advancing critical metal applications and harnessing information and communication technology to accelerate the adoption of low-carbon innovations [62].

## 1.3 Design of Networks for Zero-Carbon Facilities

In order to facilitate the spread of environmentally friendly innovations and the change in power systems, the underlying basis of the low-carbon network grid is crucial. According to an analysis of relevant, highly cited articles from the IEN corpus, the primary focus of academics is on planning the coordinated expansion of power grids and other energy infrastructure.

Our literature collection shows the focus points of zero-carbon infrastructure network design research in Fig. 3. Investigations of electrical networks focus on solar generation installations and the vast power grid, as well as power generation and distribution infrastructure. Environmental characteristics and generating potentials influence power plant siting and capacity allocation decision models, whereas power grid design focuses on efficiency, reliability, and flexibility. Integrated energy systems, which combine many energy sources, frequently involve careful assessments of electricity, heating, and cooling. Scholars have examined on-grid and off-grid integrated energy systems. Interconnected energy setups with external energy networks have been studied at individual structures, community clusters, and regional sizes. In contrast, autonomous energy systems operate without external energy networks, making them important in distant areas such dry expanses and isolated islands [63–65].

The existing literature exhibits an absence in terms of an extensive review on modeling frameworks that effectively encompasses crucial elements such as carbon neutrality, optimal ecological and financial benefits, and the interplay between production and consumption. This study is of great importance as it introduces a technical framework and a universal paradigm that successfully provides guidance for the creation and management of low-carbon systems.

The review presented provides significant insights for researchers in academia, policymakers, and energy administrators. It equips them with crucial knowledge necessary for the development of effective and sustainable low-carbon integrated energy infrastructures. This research offers a thorough basis for informed decision making by examining the intricate aspects of elements such as carbon neutrality, ecological and financial efficiency, and the partnership between

**Table 1** Comparison of proposed review with respect to other works

| Refrences | Modeling | Prediction | Optimization | Forcecasting | Futuristic | Applied |
|---|---|---|---|---|---|---|
| [66] | ✓ | × | ✓ | × | × | × |
| [67] | ✓ | × | × | × | × | ✓ |
| [3] | ✓ | ✓ | × | ✓ | × | × |
| [68, 69] | ✓ | × | ✓ | × | × | × |
| [19, 70] | ✓ | ✓ | × | × | × | ✓ |
| [71, 72] | × | ✓ | × | × | × | ✓ |
| [73, 74] | × | × | × | ✓ | × | ✓ |
| [75] | ✓ | × | ✓ | × | ✓ | × |
| Proposed | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

production and consumption. The suggested technological framework and overarching paradigm provide further guidance for the design and administration of innovative energy systems. This assessment aims to provide stakeholders from many sectors with the necessary knowledge to facilitate the development of efficient and ecologically sustainable energy solutions. Moreover, this study provides a critical assessment of current paradigms and investigates alternative technologies in this field, addressing a significant void in the existing body of work. The importance and primary contributions of this study are as follows:

1. In this study, we delve into a comprehensive analysis of the architecture and operations of IENs with a primary focus on mitigating carbon emissions. Our investigation places a strong emphasis on harnessing the utmost financial and ecological benefits attainable through these networks. By merging cutting-edge research with real-world applications, we aim to pave the way for a more sustainable and environmentally conscious energy landscape.
2. This study also presents crucial mechanisms aimed at achieving the seamless synchronization of energy supply and consumption within IENs. We provide a comprehensive summary of these vital mechanisms, shedding light on their role in optimizing energy utilization. Furthermore, we delve into uncharted territories by investigating emerging challenges that arise from the widespread adoption of zero-carbon sustainable energy sources networks within IENs. Our exploration of these new frontiers aims to uncover innovative solutions for a greener and more sustainable energy future.
3. This intriguing study not only uncovers essential insights into low-carbon design and implementation but also offers a stepping stone for future investigations. By summarizing the noteworthy challenges, generic models, and cutting-edge solution innovations, we provide a robust foundation for further exploration in the realm of sustainable energy systems. Our research paves the way for more comprehensive and advanced modeling processes, setting the stage for transformative developments in the pursuit of a greener and environmentally responsible future.

**Fig. 1** Aspects evaluated in research on the path to zero-carbon transformation

The subsequent sections of this paper are structured as follows: In Sect. 2, the Generic Design of Integrated Energy Networks is delineated. Section 3 elaborates on the Innovation and Design of Management and Operations for low-carbon IENs. Section 4 delves into the Flexibility Provisions within low-carbon IENs. Additionally, Sect. 5 offers an overview and recapitulation of Strategies for the Planning and Implementation of low-carbon IENs. The paper culminates in Sect. 6, where conclusions are drawn and perspectives are provided.

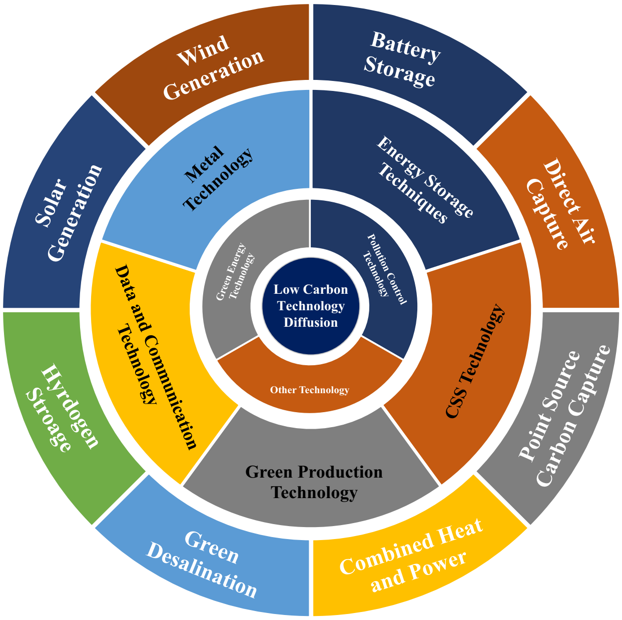

**Fig. 2** Technologies explored in existing literature for zero-carbon

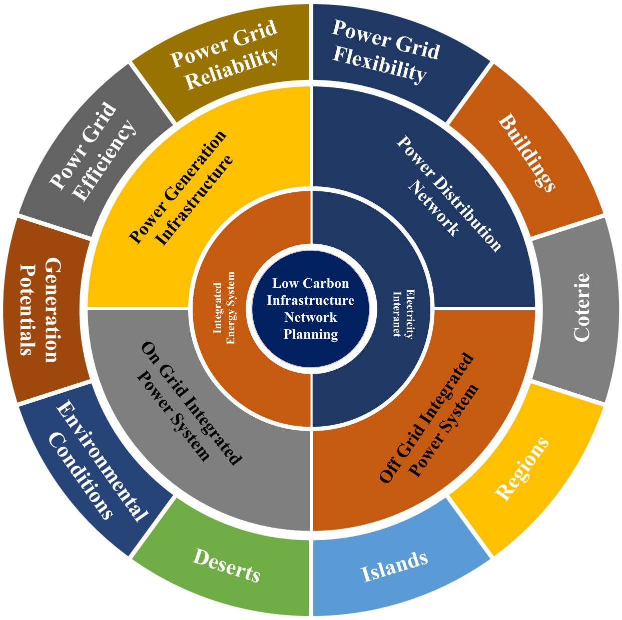

**Fig. 3** Designs for networks of low-carbon technology are the subject of the investigation

## 2 Generic Design of Integrated Energy Networks

IENs are the advanced systems that combine diverse energy sources, storage technologies, and demand-side management approaches to optimize the utilization, distribution, and effectiveness of energy. The primary objective of these networks is to improve the dependability, eco-friendliness, and economic viability of energy generation and consumption [66].

In the work by the authors of reference [76], they introduced a IENs system that was practically developed. This system aimed to initially convert PV and wind power into electrical power and subsequently store and distribute it via a shared bus voltage. Nonetheless, the surge in renewable production and its integration into the grid presents challenges for IENs on a global scale. To handle this, the emphasis of the study discussed in [77] centers on active power management through a hybrid power system. This approach concentrates on regulating energy generation through bidirectional power converters on the energy generation side. Additionally, the study implements a boost converter for maximum power point tracking control. A separate investigation directs its attention to active energy control on the power production front. This research delves into the advantages stemming from the integration of supercapacitors within a hybrid storage system [78, 79]. Numerous impactful scholarly contributions are evident in the works cited as [80–83]. IENs demand a diverse array of feeding, production, and conversion mechanisms to achieve seamless integration and deployment of thermal, photovoltaic, natural gas, and electrical power. Figure 4 illustrates the operational architecture of an IENs, showcasing its intricate workings and interconnected components.

In the process of setting up IENs, it becomes imperative to devise modules and construct a pragmatic architecture based on operational zoning. The fundamental module functions of IENs must focus on the following building blocks:

1. *Energy supply network* The core purpose of this component is to serve as the energy hub, facilitating the import of energy from external sources to power the entire network. In practical operation, the strength of the IENs lies in its energy supply module, which offers a diverse array of energy sources. For instance, this module can directly and seamlessly provide primary energy sources such as natural gas and coal to the IENs. Additionally, it plays a crucial role in supporting the operational procedures of IENs that rely on electricity as their main energy source.
2. *Energy transformation network* In order to effectively respond to the fluctuating energy demand, IENs need to be equipped with the capability to convert between different energy sources. This energy transformation process can be broadly categorized into two main groups: The first subset includes sustainable power generation networks, encompassing photovoltaic panels, wind turbines, and hydroelectric dams. These sources harness renewable energy and play a pivotal role in the generation of sustainable power. The second category consists of combined heat and power (CHP) or combined cooling, heating, and power (CCHP) systems. Within this framework, internal combustion engines, gas rotors, micro-fuel propellers, fuel cells, and Stirling engines are the primary

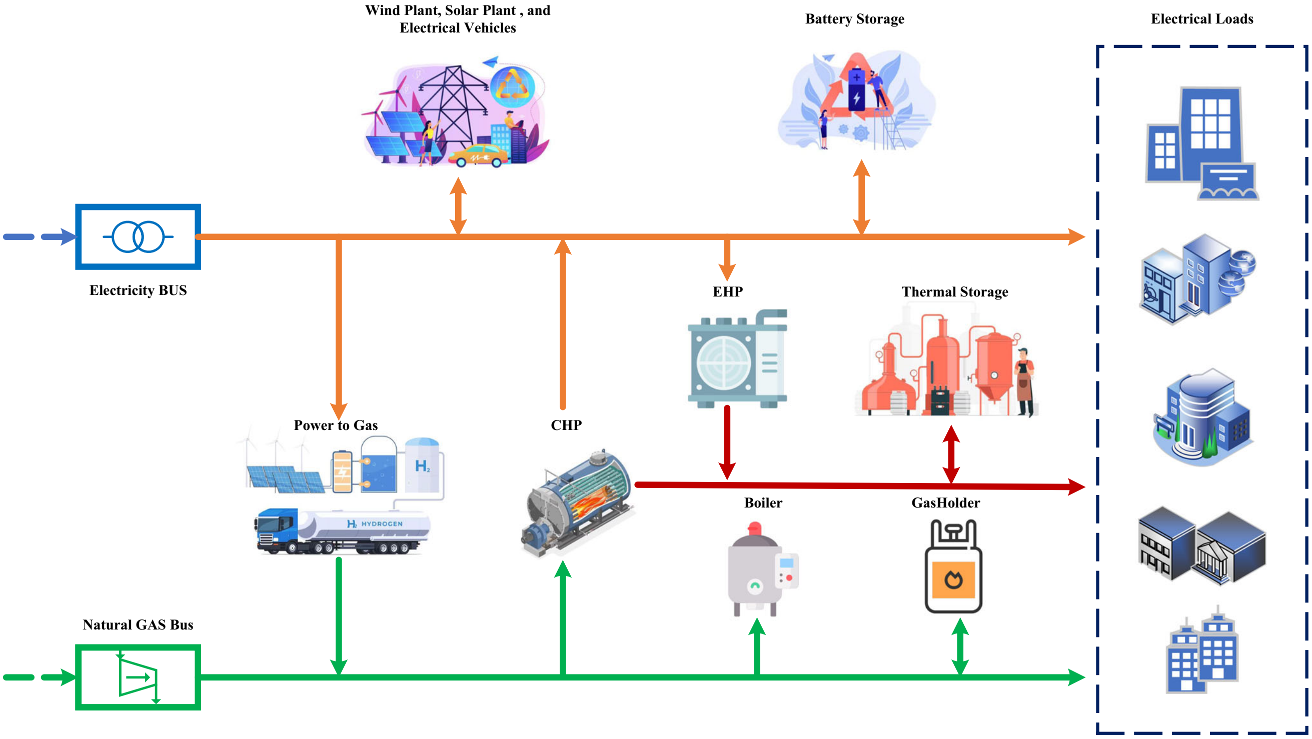

**Fig. 4** Integrated energy networks operational layout [67]

motors responsible for efficient energy conversion. These technologies enable the simultaneous production of electricity, heat, and cooling, making them highly versatile and resourceful components of the energy transformation network.

3. *Energy dispatch network* All kinds of energy, including the electric grid, thermal network, chilling network, and fuel network, will be dispatched to the consumer side through the IENs in a variety of formats.
4. *Consumption network* The main beneficiaries of the energy network are electrical customers, which include a diverse range of users, such as commercial, corporate, and residential electricity consumers. The user module takes center stage in the utilization of power within the functioning of IENs, addressing the specific requirements and demands of these end users. Additionally, the IENs are designed with the flexibility to handle variable loads, allowing for load reduction, load transference, and load transformation as needed. This adaptability ensures optimal efficiency and effectiveness in managing the fluctuating energy demands of the system.

## 3 Innovation and Design of Management and Operations of Low-Carbon IENs

### 3.1 Novel Issues

IENs bring about a revolutionary shift in the conventional approach of designing and operating individual energy modules. The network design for generic IENs encompasses linked nodes that effectively facilitate the coordination of power generation, distribution, and consumption across many sources and industries as illustrated in Fig. 5. By interconnecting these modules and leveraging their complementary functions, IENs unlock the potential to harness multiple power sources more efficiently, leading to heightened productivity and adaptability. However, the unique characteristics of IENs, such as the intricate integration of diverse power generation methods and the escalating unpredictability of source loads, pose considerable challenges for their planning and implementation. Moreover, the increasing demand for environmental sustainability and the need to maintain low-carbon emissions further add to the complexity

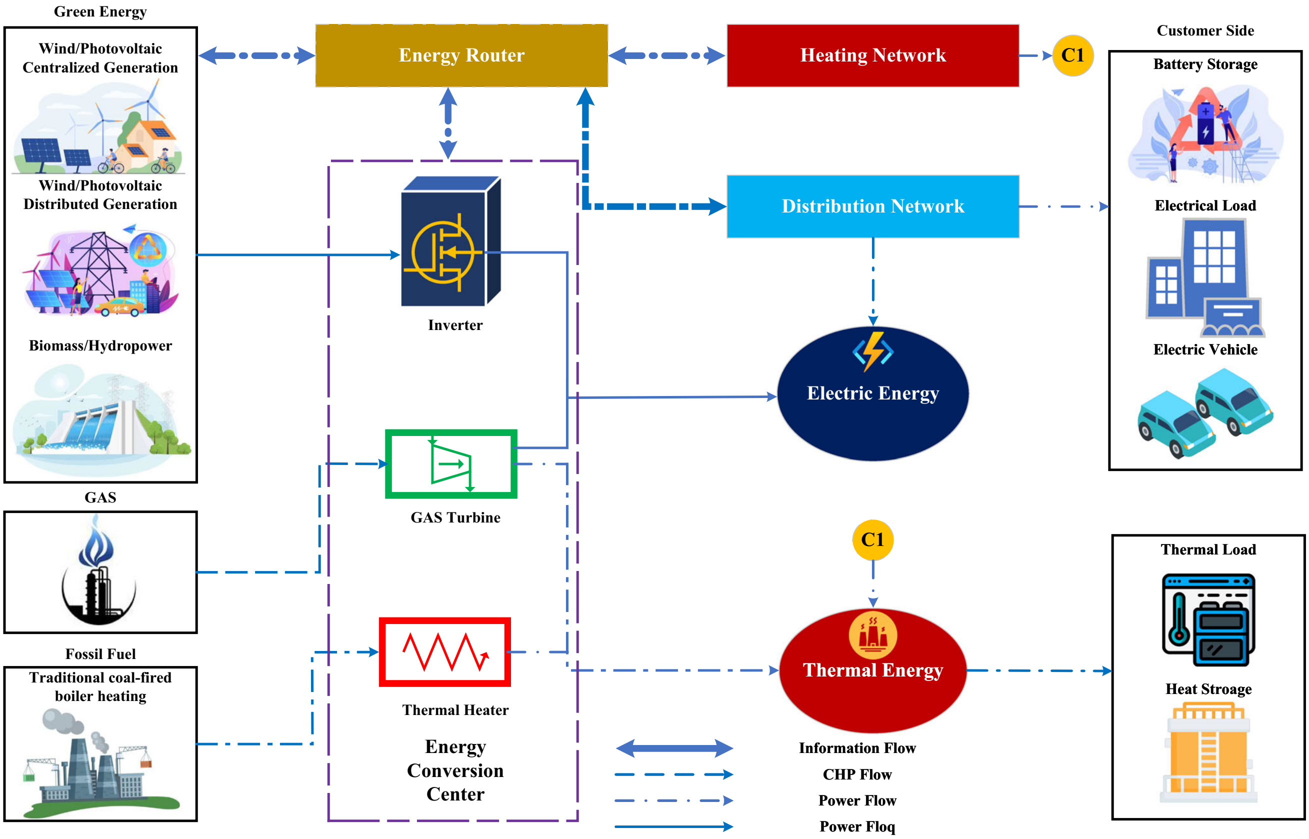

Fig. 5 Network architecture for generic IENs [84]

of designing effective and eco-friendly IENs. Meeting these challenges head-on will pave the way for a greener and more resilient energy future.

1. At the load end of IENs, there is a growing concern regarding the predictability of power consumption. The increased unpredictability of consumer power demands in IENs arises from the fact that customers have diverse energy requirements, encompassing electricity, cooling, and heating, unlike the uniform demands in conventional power grids. As a result, conventional dispatching networks face significant challenges in precisely accommodating the fluctuating system loads in IENs. This variability poses a unique set of obstacles for effectively managing and balancing the energy distribution within the network.
2. The increase in the number of IENs has led to a notable rise in the unpredictability of energy supply. The increasing significance of sustainable energy sources, such as wind power and solar electricity generation, inside IENs results in a more pronounced and impactful contribution from these sources. Nevertheless, the observed instability is not a result of an intrinsic flaw in their integration process. Instead, it is a direct outcome of their amplified representation, which magnifies their impact inside any given system, especially an IEN. This variability in energy sources creates challenges in maintaining a consistent power supply and meeting the growing demands for energy. The increasing fluctuations in energy supply call for innovative solutions to ensure a reliable and continuous power provision to cater to the expanding needs of consumers.
3. Simulating the functionality of IENs is crucial due to the diverse range of energy sources present within the system. With the complexity of operational settings stemming from this variety of energy sources, it becomes essential to employ simulation technology. By conducting operational modeling through simulation, we can obtain valuable operation statistics for the planning process under various scenarios. This allows us to thoroughly evaluate the logic of the planning process and assess its effectiveness in managing the intricacies of IENs. Through simulation, we gain valuable insights into the performance and behavior of IENs, enabling us to optimize their design and enhance their overall efficiency.
4. The cooperative multi-agent scheduling in IENs has evolved into a highly interdependent system where components are intricately linked rather than loosely asso-

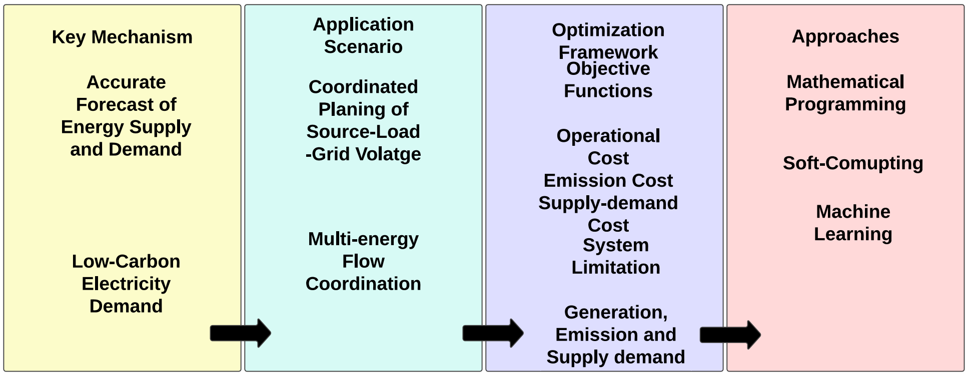

**Fig. 6** The interconnected components and collaborative functioning of IENs system

ciated. The connections among these components are so tightly integrated that any disruption or change in one link can propagate throughout the entire system via these coupling elements. As a result, IENs no longer lend themselves to single-agent plans or actions since the collaborative nature of the network requires the active participation and coordination of multiple agents. The tight coupling of components necessitates a collective and synchronized approach to achieve optimal functioning and efficiency within IENs.

## 3.2 Common Models

Optimal modeling of IENs bears resemblance to that of traditional power systems, as it necessitates the development of a statistical model capable of explaining the system's operational characteristics based on the functioning principles and initial conditions of its individual components. This process entails defining the modeling scenario, planning objectives, and constraints. In the implementation scenario for IENs, a key focus lies in coordinating various resources, networks, demands, storage, and diverse power flows. Achieving this objective entails leveraging cooperative management, which involves the harmonization of power networks, loads, and storage—a concept often referred to as the source–grid–load–storage triangle. Furthermore, IENs planning emphasizes the preservation of power supply reliability while also considering the collaboration of multi-energy channels to enhance the absorption of green power and bolster multi-energy complementing capacity. To visually depict the IENs optimization framework, Fig. 6 provides an illustrative representation of the interconnected components and their collaborative functioning within the IENs system.

### 3.2.1 Decision Variables

In this context, we designate the machinery status and power usage as the operative variable $ov_{k,l,t}$, while the GHGE rate and sustainable power usage serve as environmental parameters $ev_{k,l,t}$. The term "operative variable" in this context pertains to the quantity of electrical energy that is used or utilized by a certain equipment, system, or process while the term environmental variables is of utmost importance in order to optimize power consumption, enhance energy efficiency, and facilitate the design of systems. Additionally, we define the changing patterns of sustainable energy power production output at the supply and power needs at the load as fluctuating variables $fv_{k,l,t}$, which refers to a situation where the power demand varies over time.

### 3.2.2 Common Objective Functions

In power network optimization, the primary objective function typically aims to minimize the overall cost of the generation network, emphasizing energy efficiency, and affordability [85–91]. To address GHGE, this objective function is extended to encompass environmental concerns, such as limiting carbon emissions and optimizing the proportion of sustainable energy in the generation mix [92, 93]. During the low-carbon design and implementation of IENs, careful consideration is given to both environmental and financial gains, with the ultimate goal of enhancing ecological and economic security performance. The focus remains on satisfying consumers' energy needs while increasing the utilization of sustainable power sources. In general, combinatorial optimization functions are employed in frameworks that do not take carbon trading into account, ensuring a holistic approach to optimizing the energy network.

$$\begin{cases} \min f(cost) = \sum_{i=1}^{n} f_i \\ \qquad + f(solar) + f(wind) + f(hydro) + f(misc), \\ \min e(emission) = \sum_{i=1}^{n} e_i - e^m, \\ \max \alpha_1, \\ \ldots\ldots \\ \max \alpha_i. \end{cases} \tag{1}$$

In Eq. (1), the variable $f$ represents the total cost, while $f_i$ represents the individual components' costs, excluding car-

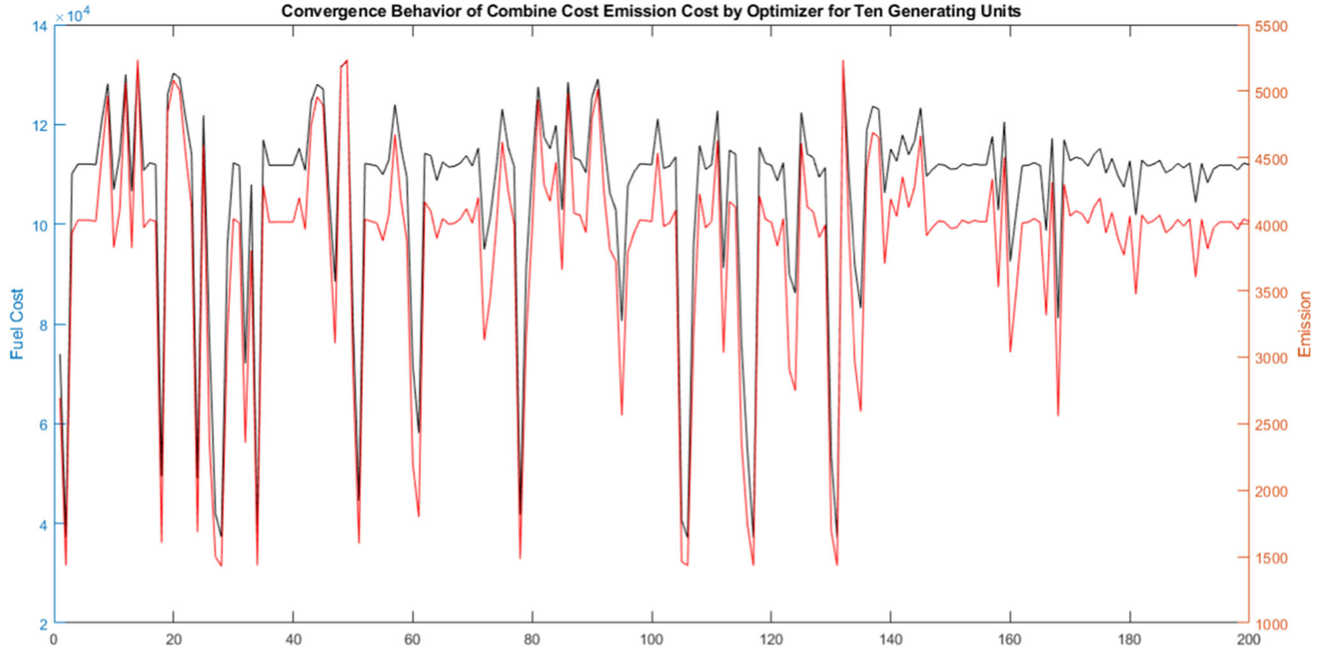

**Fig. 7** Convergence plots of whale optimization algorithm [91]

bon trading expenses. The variable $e_i$ denotes the carbon emissions associated with each energy production component, while $e^m$ reflects the reduction in carbon pollutants achieved through carbon reduction devices. Additionally, the consumption rates of different sustainable energy sources are represented by $\alpha_1 \ldots \alpha_i$. The cost function in the production of electricity pertains to the correlation between the output of a power generating unit and the corresponding cost incurred in producing that specific amount of power. On the other hand, the emission function in economic dispatch serves as a mathematical depiction of the connection between the output of a generating unit and the quantity of emissions generated as a consequence of producing said power. In the research conducted by Ahmed et al. [91], the network's demand is set at 2000 MW. The outcomes of simulations employing the whale optimization algorithm for the equation provided in (1) are visually presented in Fig. 7. The study undertook two hundred iterations, and the proposed computational framework yielded encouraging results in dealing with non-convex functions, including cost and emission pollutants.

While the utilization of the whale optimization algorithm yielded impressive outcomes, achieving the optimal solution for generation cost and emission levels becomes notably challenging in the presence of system constraints posed by IENs. In the research conducted by Ahmed et al. [89], a more intricate system was investigated, incorporating stringent limitations like valve-point loading effects and ramp-rate constraints. The optimal results obtained from this study are depicted in Fig. 8. It is noteworthy that evolutionary-based optimization approaches manage to achieve global optima while adhering to all the stipulated system constraints.

In the current research on IENs, the fundamental concepts of low-carbon management and operation involve incorporating carbon pollution or emissions trading costs as relevant elements, variables, or constraints in the design and implementation of the IENs. Subsequently, a system function optimization strategy is proposed, considering both ecological and economic factors in achieving the desired goals [94, 95]. This approach aims to strike a balance between environmental sustainability and financial viability while optimizing the overall performance of the IENs. Typically, IENs have the following objective function:

$$\begin{aligned}\min f(misc) = {} & f_{operational} + f_{carbon\ capture} \\ & + f_{supply-demand}.\end{aligned} \tag{2}$$

In Eq. (2), the variable $f$ corresponds to the total cost, which can be broken down into several components:

- $f_{operational}$ represents the overall operating expenses, encompassing machinery operation and servicing costs.
- $f_{carbon\ capture}$ refers to the ecological expenses, which include the expenses associated with decarbonization methods (e.g., carbon capture), the cost of emissions trading, and penalties related to underutilized sustainable power sources.
- $f_{supply-demand}$ accounts for the supply–demand cooperation expenses, which comprise the dynamic load

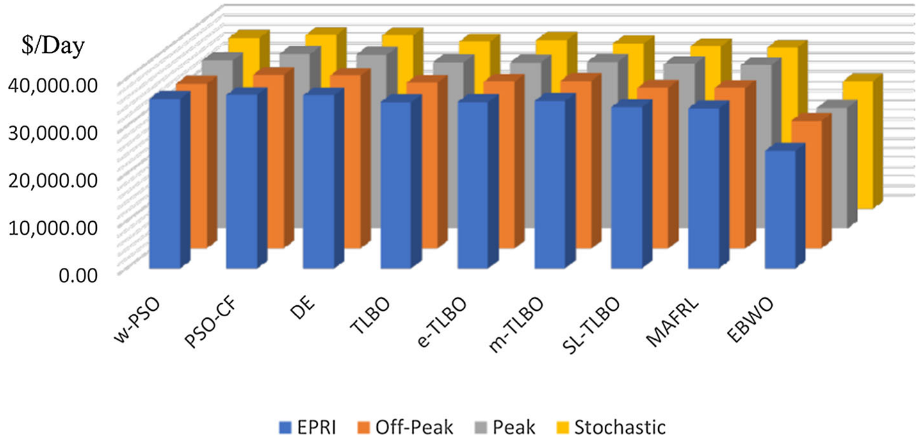

**Fig. 8** Cost and emission results of [89]

dispatching expenses and the compensatory expenses associated with load management.

This equation allows for a comprehensive assessment of the various cost factors involved in optimizing the efficiency and performance of the energy system while taking into account both ecological and economic considerations.

### 3.2.3 System Limitations

Once the durability and operational constraints are taken into consideration, it is essential to account for ecological conservation constraints and supply–demand cooperation restrictions in the process of designing and implementing low-carbon IENs. Several common limitations that need to be considered are as follows:

$$\begin{cases} G\left(ov_{k,l,t}, fv_{k,l,t}\right) \leq \lambda_1, \\ H\left(ov_{k,l,t}, fv_{k,l,t}\right) \leq \lambda_2, \\ K\left(ov_{k,l,t}, fv_{k,l,t}, ev_{k,l,t}\right) \leq \lambda_3, \\ M\left(ov_{k,l,t}, fv_{k,l,t}\right) \leq \lambda_4. \end{cases} \quad (3)$$

In equation (3), the function $G\left(ov_{k,l,t}, fv_{k,l,t}\right)$ encompasses the operational limitations, which encompass requirements related to electricity production, transmission, and fuel acquisition. The function $H\left(ov_{k,l,t}, fv_{k,l,t}\right)$ accounts for reliability limitations, including power balancing and capacity augmentation. Furthermore, the function $K(ov_{k,l,t}, fv_{k,l,t}, ev_{k,l,t})$ incorporates ecological conservation limitations, such as constraints on carbon emissions and the proportion of sustainable power in the overall energy consumption. The function $M\left(ov_{k,l,t}, fv_{k,l,t}\right)$ represents supply–demand cooperation limitations, encompassing constraints on dispatchable production and demand responsiveness.

To ensure the operational compatibility of devices and power grid characteristics, we consider the variable $\lambda_1$, while the steady-state operating range, associated with the system's power equilibrium, is denoted by $\lambda_2$. Additionally, considering carbon cap limitations and sustainable power utilization rates, $\lambda_3$ represents an ecological limit. Lastly, the coordinated supply and demand adjustment limit is represented by the variable $\lambda_4$. All these elements are critical in defining and addressing the various limitations encountered in optimizing the performance and efficiency of IENs while simultaneously ensuring ecological and economic sustainability.

### 3.2.4 Approaches

The design of IENs is often approached as a nonlinear programming task. Traditionally, linear programming techniques or heuristic methods are employed to find optimal solutions. Standard designs establish the fundamental framework for managing and operating low-carbon IENs, but customization is essential to address specific challenges in diverse implementation scenarios.

Tailoring decision factors, objective functions, and constraints allows for addressing particular issues, such as carbon trading, leveraging power synergies, optimizing load management, promoting sustainable energy consumption, and adapting to dynamic load variations. By incorporating these tailored elements, IENs can be optimized to suit specific requirements and achieve an effective balance between ecological sustainability and operational efficiency [96].

## 4 Flexibility Provisions in Low-Carbon IENs

As mentioned earlier, IENs exhibit adaptability through various subsystems, which are situated on the generation, distribution, and demand sides. These subsystems form the major components of the flexibility options explored in this study. Additionally, the research delves into the flexibility possibilities arising from innovative advancements, such as strategically positioned power storage devices that can efficiently operate on either side of the power systems.

Furthermore, a comprehensive assessment is conducted of primary governance frameworks, such as power system cooperation, which have already demonstrated or are expected to possess the capacity to enhance the flexibility of IENs. By examining and understanding these diverse sources of adaptability, we gain valuable insights to enhance the responsiveness and resilience of IENs to varying operational conditions and challenges.

## 4.1 Possibilities for Load Flexibility

Within IENs, load-side provisioning is widely recognized for its significant flexibility. This flexibility stems from the ability to influence end-consumer behavior through both monetary and non-monetary incentives, as well as diverse pricing mechanisms. Such alterations in consumer behavior can lead to persistent changes, like improved power performance, or intermittent changes, such as shifting power usage from peak to off-peak time frames.

Load-side flexibility processes are generally considered the most practical and cost-effective approach to enhance IENs' flexibility and seamlessly integrate intermittent power sources. Several key types of flexibility within the load-side are discussed, including demand or load response, power management strategies, and unique methods of energy utilization. By harnessing these types of flexibility, IENs can effectively adapt to fluctuations in power supply, optimize resource utilization, and enhance the overall efficiency and reliability of the energy system.

### 4.1.1 Demand Response

Demand response (DR) is a consumer-side flexibility option that involves adjusting power consumption patterns in response to dynamically changing pricing and incentives. Well-designed DR programs enhance the flexibility, responsiveness, and adaptability of power consumption based on financial signals. Depending on the clients' price elasticity of energy demand, these modifications may entail reducing energy usage, shifting energy consumption patterns, or a combination of both. A flexibility index quantifies the variation in energy consumption in relation to relative pricing, with higher indices leading to more significant shifts in consumption patterns. Greater self-elasticity values result in more effective peak shaving and valley filling, leading to a smoother daily load profile [97–99].

DR interventions can be incentive-based or price-based. The first type involves variations in power usage driven by non-price indicators, while the second approach employs economic incentives to influence consumer behavior. Reward-based DR encompasses demand-side programs such as load management of IENs, demand auctions or buyback schemes, and rescue DR. On the other hand, price-based DR primarily includes time-of-use tariffs, peak pricing, peak time rebate, and real-time pricing programs [100–102].

Beyond its adaptability, DR offers numerous other benefits, extensively researched in this field. Despite the recognized advantages of DR, its implementation rate in many power systems remains limited due to the absence of an appropriate market structure, reliable planning tools, and robust control and monitoring procedures. Overall, some of the significant benefits of DR are as follows:

1. DR plays a crucial role in facilitating the adoption of IENs and mitigating energy supply fluctuations. It achieves this by effectively reducing or transferring loads in response to variations in energy output. By actively responding to changes in energy availability, DR helps to stabilize the energy supply, ensuring a more consistent and reliable power provision within the IENs system. This capability not only enhances the overall performance and resilience of the network but also encourages the seamless integration of intermittent renewable energy sources, contributing to a more sustainable and efficient energy landscape.
2. Through DR, energy usage can be rapidly adjusted, enabling a more efficient and responsive ramping rate compared to larger energy plants. This dynamic responsiveness of DR allows for quick adaptations to changes in energy demand, facilitating a smoother and more controlled energy supply. Unlike traditional larger energy plants, which may take longer to adjust their output, DR's instantaneous alterations in energy consumption contribute to a more efficient utilization of resources and a more agile response to fluctuating energy needs. As a result, DR plays a vital role in optimizing energy distribution and ensuring a more reliable and flexible energy system within IENs.
3. By employing DR in IENs, the capacity requirements of the network can be effectively met while simultaneously reducing emissions. DR allows for a more flexible and adaptive management of energy consumption, enabling the network to respond efficiently to fluctuations in demand. This responsiveness ensures that the energy supply matches the real-time needs of consumers, optimizing the utilization of available resources. As a result, the implementation of DR in IENs helps to minimize the reliance on conventional energy sources, which often contribute to higher emissions. By aligning energy consumption with actual demand, IENs can rely more on sustainable and low-carbon energy sources, leading to reduced greenhouse gas emissions and a more environmentally friendly energy system. DR thus plays a vital role in enhancing the sustainability and eco-friendliness of IENs, contributing to a greener and more efficient energy landscape.

4. Promoting the participation of DR in carbon trading markets can lead to a notable reduction in both supply and location-specific market power. As DR adapts its energy consumption patterns in response to time-varying rates, the influence of energy producers on wholesale rates is restricted. This decreased market power of energy producers contributes to a decline in average wholesale costs, fostering a more competitive and dynamic energy market. Additionally, the engagement of DR in carbon trading markets creates a more stable environment, particularly in terms of peak pricing. The ability of DR to respond to carbon pricing signals helps mitigate price fluctuations during peak demand periods, leading to a more predictable and controlled energy pricing system. By involving DR in carbon trading, the energy market gains increased efficiency, reduced monopolistic practices, and enhanced price stability, ultimately benefiting consumers and supporting the transition toward a more sustainable and environmentally responsible energy ecosystem.

While the concept of load profile is well established, its widespread implementation has been hindered by several challenges. Despite the numerous benefits it offers, the adoption of demand response (DR) faces significant obstacles, primarily related to its management and optimal utilization [103–105]. Outlined below are some of the key obstacles that impede the successful implementation of carbon trading in IENs:

- Management complexity: Integrating DR into existing energy systems requires sophisticated management strategies, including real-time monitoring, decision making, and coordination. The complexity of managing diverse energy resources and customer demands poses challenges to seamless implementation.
- Information barriers: Effective DR relies on accurate and timely information regarding energy prices, demand patterns, and customer preferences. The lack of transparent and accessible data can limit the efficient functioning of carbon trading mechanisms.
- Regulatory framework: The absence of well-defined regulatory frameworks and standards for carbon trading in IENs can hinder its widespread adoption. Uncertainty in policy and legal aspects may deter stakeholders from actively participating in carbon trading markets.
- Market design: Designing efficient and fair carbon trading markets requires addressing issues like market power, price manipulation, and market concentration. Creating a balanced and competitive marketplace can be challenging.
- Technology integration: Incorporating DR into existing energy infrastructure often demands technological upgrades and seamless integration. Compatibility issues and technological constraints can slow down the implementation process.
- Customer engagement: Successfully implementing carbon trading requires active engagement and cooperation from end users. Raising awareness and incentivizing participation among consumers may be challenging.
- Risk and uncertainty: Participants in carbon trading markets face risks associated with price fluctuations, demand unpredictability, and regulatory changes. Addressing risk and uncertainty is crucial for market stability.

#### 4.1.2 Smart Appliances and Home Automation

The incorporation of intelligent appliances and home automation systems has become a significant catalyst for load flexibility in integrated energy networks. Load flexibility is the capacity to adjust energy consumption patterns in reaction to several conditions, such as fluctuations in power pricing, variations in supply and demand, and the stability of the grid. This novel methodology enables users to proactively regulate their energy consumption while also contributing to a more environmentally friendly and optimized energy system. At the core of this paradigm are intelligent appliances that incorporate sensors, connection, and automation functionalities. These gadgets, which encompass a variety of smart thermostats, freezers, and lighting systems, establish real-time communication with one other as well as external systems. This interaction facilitates automated adaptations in response to grid circumstances and user preferences. In addition to their functionality, home automation systems function as coordinators, harmonizing gadgets and appliances within a residential setting. These systems effectively optimize energy use by intelligently managing preferences and schedules. There are several benefits associated with the integration of smart appliances and home automation systems into load flexibility methods. Primarily, these devices facilitate demand response programs by automatically reducing energy use during periods of high demand. As an illustration, a technologically advanced thermostat has the capability to make subtle modifications to temperature settings during periods of peak demand, thus mitigating strain on the electrical grid. Moreover, these systems dynamically optimize energy use by leveraging real-time pricing information. Consumers may optimize their power use and take advantage of reduced electricity costs by strategically arranging energy-intensive activities such as laundry and dishwashing during periods of low demand, commonly referred to as off-peak hours.

The utilization of smart appliances and home automation systems yields substantial improvements in energy efficiency. These solutions are designed to maximize operational efficiency by reducing standby power consumption and promoting judicious usage of equipment. Additionally, they contribute to the stability of the grid. During situations characterized by increased demand or supply limitations, these systems have the ability to collectively decrease energy use in order to mitigate the risk of grid overload. Notwithstanding these advantages, the utmost priority is still user convenience. For example, intelligent lighting systems have the capability to adjust the intensity of illumination in response to ambient light conditions, all while ensuring user contentment [106, 107].

One sometimes disregarded benefit of these systems lies in their capacity to integrate with renewable energy sources. The integration of home automation systems with renewable energy sources, such as solar panels, allows for a smooth synchronization between these technologies. Appliances have the capability to be designed in a manner that allows them to function during periods of peak renewable energy output, thereby optimizing self-consumption. Furthermore, via the strategic scheduling of energy-intensive appliances, home automation systems play a role in peak shaving, which aids in the equitable distribution of energy loads across different periods of the day [108].

#### 4.1.3 Electric Vehicle (EV) Charging Flexibility

The concept of EV charging flexibility pertains to the capacity of charging EVs to be adaptable and responsive to several conditions, including grid demand, energy pricing, and the availability of renewable energy sources. This idea recognizes the potential for EVs to be charged at various times, prices, and places in order to maximize the preferences of car owners and meet the requirements of the larger energy system. The use of intelligent charging techniques enables EVs to be charged during periods of low-power demand, such as off-peak hours. This practice aids in achieving a more equitable distribution of the grid load. In addition, the flexibility of EV charging may be synchronized with periods characterized by substantial renewable energy generation. This synchronization enables EVs to function as a useful form of energy storage, as they can absorb surplus energy and subsequently discharge it to the power grid during moments of heightened demand. This method not only improves the overall efficiency of the power grid but also facilitates the incorporation of renewable energy sources and encourages sustainable mobility options [109, 110].

#### 4.1.4 Peer-to-Peer Energy Trading

Peer-to-peer energy trading is an emerging paradigm that embodies a decentralized and inventive method of facilitating energy transactions. This novel technique enables people and enterprises to engage in direct exchanges of excess energy within a localized community setting. This concept utilizes blockchain technology and smart contracts to facilitate transactions that are safe, transparent, and automated. Individuals who possess renewable energy sources, such as solar panels, have the opportunity to engage in the sale of surplus energy to their nearby residents, so cultivating a notion of self-sufficiency in energy production and bolstering communal adaptability. Peer-to-peer energy trading fosters effective energy consumption and facilitates the expansion of distributed energy resources by removing intermediaries and empowering customers to choose their own pricing. This strategy not only facilitates the active participation of individuals in the energy market but also helps to the development of a more sustainable and locally oriented energy environment [111].

The majority of the IENs are planned in a centralized manner, making them inappropriate for the actual heterogeneity and dispersal of demand. Upcoming tools, such as blockchain computing and distributive market designs, are anticipated to unleash the tremendous opportunities of low-carbon trading [74]. Furthermore, developing a business case for carbon trading versus demand response in the present day is extraordinarily challenging. Integrating demand into electricity markets is acknowledged to promote societal welfare. It can be challenging to design a business model that collects adequate people's benefits with sufficient predictability to make the firm viable and justify expenditures in infrastructures when the social benefit is spread among numerous firms [71, 112, 113]. A greater level of market adoption for carbon trading may result in the emergence of possible conflicts of interest. For instance, certain power plants that take part in reserve capacity exchanges may be opposed to the introduction of low-carbon trading policies due to the potential for losses in the amount of money they make from those markets. Carbon trading will take over the obligation for regulation and ramping if the capacity value and availability in times of need for trading is very large. This would result in a decrease in income for peaking power plants [114–116]. In addition, policies to reduce carbon emissions place a significant emphasis on customer behavior, which can be notoriously difficult to forecast. Differing end users may place different importance on certain factors. For instance, some customers might not even give the idea of lowering their energy consumption any consideration at all, while others would be interested in taking part in low-carbon programs but be concerned about their security. External factors, such as the weather or any other element, can have a variety of effects on the demand curve. These effects can fluctuate over time. As a result of all of these factors, demand behavior might not be appropriate for standard low-carbon economic models [72, 117–119].

Generally, the development of new regulatory rules for carbon-free energy is urgently required if one wishes to affect the course of the long-term evolution of IENs. These kinds of policies are extremely important in the process of designing adaptive systems that are able to effectively deal with a wide variety of dynamics present in the systems. It is essential to recognize the fact that efficient institutional arrangements accurately reflect the roles and duties of market participants in order to effectively manage the flexibility possibilities supplied by multiple options in the upcoming energy market. Overcoming these obstacles requires collaborative efforts from policymakers, energy providers, regulators, and consumers. Implementing supportive policies, investing in technology, promoting customer awareness, and fostering market competition can pave the way for a more successful integration of carbon trading in IENs.

# 5 Strategies for Planning and Implementation of Low-Carbon IENs

## 5.1 Technical Support Depending on the Implementation Context

Alongside the evolving challenges faced by IENs, the planning architecture and standard designs play a crucial role in the successful decarbonization and operation of these networks. Accurate predictions of power demand and supply, coupled with the establishment of a carbon-free electricity market, are considered essential innovations in achieving the goal of decarbonization within IENs. The planning architecture provides a blueprint for optimizing the integration of renewable energy sources, demand response strategies, and energy storage technologies. By carefully designing the network layout and considering various factors such as energy demand patterns, geographical characteristics, and renewable energy availability, IENs can be better prepared to handle carbon-free power generation.

Furthermore, accurate predictions of power demand and supply are vital for efficient energy management within IENs. By anticipating fluctuations in energy demand and supply, the network can adapt in real time, enabling optimal utilization of renewable energy resources and efficient load management. The establishment of a carbon-free electricity market is another crucial innovation. Creating a marketplace where carbon emissions are factored into pricing and incentives can encourage the adoption of clean energy sources and incentivize carbon reduction efforts. Such a market would promote the deployment of low-carbon technologies, thus accelerating the transition to a sustainable and environmentally friendly energy landscape. Overall, these key innovations in planning and design, along with advancements in accurate demand and supply predictions and the establishment of a carbon-free electricity market, form the foundation for the successful decarbonization and operation of IENs, paving the way for a greener and more sustainable energy future.

### 5.1.1 Accurate Estimation of Power Production and Consumption

Research indicates that carbon dioxide footprints cannot be reduced without an extensive transition from fossil fuel-based domain to sustainable energy networks [73, 120–122]. In the meantime, the implementation of sustainable power sources will considerably increase the unpredictability of the next generation of IENs in comparison with conventional power systems. According to research, the unpredictability and stochastic fluctuation of sustainable energy has a massive price, which can be significantly decreased with an accurate forecast of the resource variation [123]. Consequently, incorporating the unpredictability of new power streams into the model development is a necessity for contemporary planning research. Wind and photovoltaic power, the two primary sustainable power sources, are influenced by wind velocity and illuminance, respectively. Combining the conditional probability features of luminance and wind velocity, it is currently normal practice to construct a stochastic output model of green energy.

The power generation of IENs is influenced by climate, location, territorial layout, and other variables. Significant studies have been conducted on the prediction of sustainable power supply. In predicting the power generation of IENs, statistical methods such as gray models (GM) and machine learning like neural networks play an important role. In [124], an emerging research system based on the exponential smoothing and GM approaches is developed to anticipate the stable level of China's power generation, thereby enhancing the theoretical analysis of power security prediction. An artificial neural network (ANN) is a potent tool for simulating photovoltaic power networks in-depth, [125] provides a description of the prevalent ANN kinds and topologies, such as multi-layer perceptron neural networks, and Elman neural networks. In terms of wind-speed energy source forecasting, [126] suggests a wind-speed forecasting model based on a genetic adaptive neural network (GANN) and improved by variational mode decomposition (VMD). This model may improve the accuracy of wind-produced energy delivery forecasts.

On the consumer side of the IEN, unlike the old distribution systems with just specified loads, a range of new demands will engage in power network dispatching. The participant's differential demand requirement and the ratio of power usage to diversified power flow will influence the capacity assignment of energy infrastructure. Therefore, analyzing the load features of IENs in wide-scale application situations is required. In predicting the power requirement of IENs, mathematical models such as GM and computer algorithms such as neural networks play a significant role. Using the GM method, [127, 128] forecast power consumption for macro-level conditions. To improve forecast precision of power usage in local settings, [129] combines feed-forward back-propagation ANN, radial basis ANN, and adaptive neuro-fuzzy interference system (ANFIS).

As a result of the recent surge in popularity of AI and data science, power requirement prediction approaches such as deep learning and supervised learning are actively used in the field of power system load forecasting, providing a new way to improve prediction performance in IENs. In [130–133], the author suggested using decentralized adaptive multi-agent technology to build a safe and effective energy system that makes use of sustainable power sources. Using a demand requirement prediction system and learning algorithm, reference [75] builds a mathematical framework of hydrogen-basedIENs and designs a power infrastructure with greater adaptability. In [134], a new incentive-based low-latency load management technique for smart grids with neural networks and supervised learning is proposed. This technique uses a deep algorithm to figure out future costs and energy needs and uses supervised learning to find the best incentive prices.

Hybrid energy control network design and management is predicated on accurate estimates of sustainable power supply and combined energy needs over several timescales. In the future, it is anticipated that the theory of artificial intelligence will increase the applicability of the IENs management and operating paradigm.

### 5.1.2 Reduced Carbon Power Market

The IENs are the most fundamental implementation paradigm for the low-carbon energy market. The electrical industry will be radically reshaped by low-carbon innovations. Consequently, a major redesign is necessary for the prospective low-power market and related regulatory structure [135–138]. The current focus of research is an examination of the carbon and energy markets' linkage strategies and operating methods. Since the Kyoto protocol went into force, numerous nations have studied and developed the carbon trading scheme, but there is currently no global standard for the trading scheme. The allotment of carbon quotas is vital and essential to the carbon emission trade. The bench-marking approach, the historic emission approach, and the bidding approach are the three types of assignment techniques. By March 2020, one global carbon market, five regional carbon markets, 16 state carbon markets, and seven carbon markets at the municipal level addressed more than 20% of overall GHGE [139].

The energy trade and carbon exchange market demonstrate a favorable and symmetrical association. Consequently, a vital precondition for the design and management investigation of IENs is the analysis of their connection and the development of a low-carbon energy market system with an appropriate operating mode. The new attributes of the low-carbon energy market relative to the conventional power industry are outlined in Table 2.

The IENs' design and management in the context of carbon credits are garnering increasing interest in the scholarly institution, and there is an abundance of associated scientific investigation outputs. A paradigm for electricity-gas-basedIENs design that incorporates wind energy and carbon credits is devised at the planning phase in [143]. A multilevel decarbonizing procedure framework including a carbon-restricted locational marginal pricing (LMP) is suggested at the administrative level in [144]. It calculates the discharge of the higher source layer and the bottom local demand layer using carbon emission flow (CEF). At the dispatch stage, [145] gives a probabilistic economic framework that takes into account both the unpredictability of wind energy and the carbon trading scheme. This framework can be used as a standard for the scientific assignment of the demand needs of wind energy IENs.

Carbon trading schemes are widely used with a variety of other concepts to improve the design, administration, and dispatch of power systems.

Reference [146] sets up a dispatching framework with carbon clean credential synchronized trading framework for virtual energy plants (VEP) platform incorporating carbon capture energy plants, energy to gas, wind and photovoltaic power facilities, and cost-based load management, breaking the existing boundaries of carbon emission trading (CET) and green credential trading (GCT). Prospective investigation and the application of green energy will demonstrate a shift toward blending centralize and distributed methods. Consequently, it is vital to encourage the emerging manner and commercial expansion of decentralization and to promote the growth and widespread application of decentralized energy. Ref. [147] provides a distinctive distributed optimized multi-energy flow (OMEF) of wide-scale IENs in a carbon trading system, which is a significant benchmark for the decentralization of power systems.

Modern research emphasizes primarily the functioning and transmitting phase of IENs modeling in the low-carbon energy market, whereas there is little study on the design stage taking carbon trading into account. The establishment of a somewhat extensive IENs planning process based on an in-depth analysis of the low-carbon electricity market remains necessary.

## 5.2 Framework of Management and Operation

Table 3 lists the important elements and their illustrative examples of goal tasks in the IENs management, operation, and dispatch model. Current models primarily attempt to decrease cost and carbon emissions to build a bi-objective programming challenge with function optimization that takes

**Table 2** The innovative features of the low-carbon IENs

| Facets | Categories | Simulation |
|---|---|---|
| Assigning carbon emissions caps [140] | Measurement by comparison | The most prevalent assignment of quotas according to the sector integrated carbon emission concentration |
| | Historic emission technique | Assignment of quotas based on the previous total emissions of firms |
| | Auction | Depending on their demands, businesses acquire quotas through bidding |
| Carbon exchange rates [141] | Unified carbon tax | Fixed pricing expressing supply and demand across the intermediate and distant terms |
| | Cost of ladder-type carbon | Carbon-emissions-dependent variable costing that reflects real-time demand and availability |
| | Cost carbon according to market settlement | Fixed price reflecting demand and supply in reality |
| Carbon exchange products [142] | Carbon emissions products | Authorization for carbon emission, incentivizing businesses to cut carbon emission prices |
| | Carbon credits products | Carbon emissions offsetting or business participation, promoting the use of decarbonization technology such as sustainable power supplies and carbon capture devices |

into account capital, administration, carbon, sustainable sources, load management, and other interconnected aspects.

On the premise of conventional elements influencing system modeling, the carbon emission permit throughout the design period is incorporated into a complete plan for the system's network and energy architecture at the planning stage. The minimum cost of capital, administration, and carbon trading is used as the optimization problem in a basic integrated energy system (IES) design model. This is done to build a multi-objective programming framework that takes both economic and environmental factors into account. In the sphere of linked organic gas and power networks and power to gas (P2G) technologies, [68] suggested a simple two-step decarbonizing operation management framework that takes into account a dual carbon trading scheme and active consumption side control. To even further lower carbon pollution, Ref. [148] revealed that electric gas-linkedIENs incorporating carbon capture may effectively account for economical and low performance, while simultaneously enhancing sustainable power accommodation.

On the basis of sustainable power, various studies construct a reduced carbon functioning paradigm for IENs at the operational level. Reference [149] developed a local power system optimization strategy that takes into account the role of clean energy use, green certificate trade, and carbon credit process. Current IENs systems have accounted for sustainable power, carbon trading, and other innovations and procedures for cutting emissions. In subsequent investigations, however, the modeling techniques might be enhanced by expanding the adaptability choices in the four aspects of supply-grid-load-storage. To deal with the intricacy and dynamic unpredictability of IENs, the effect of the prospective power industry on the power running and dispatching operations and the interface with other power systems inside the energy internet must also be considered.

## 5.3 Design Solution Approaches

Employing CPLEX, an integrated energy system optimization operational system is developed in the MATLAB/Simulink environment by leveraging YALMIP (Yet Another LMI Parser) toolkit. The rationale is that the YALMIP package may call several independent optimization algorithms, enabling the usage of uniform modeling and resolving language. The CPLEX exhibits the benefits of adaptability, speed, and dependability for tackling linear programming challenges [69]. The system developed in [150] incorporates nonlinear characteristics generated by carbon trading designs, which are turned into linear designs via segmentation linearization and resolved by running the CPLEX solver through the GAMS program. In this kind of study, the Mixed-Integer Nonlinear Programming (MINLP) paradigm is also often used. The most recent changes to ways to deal with the MINLP challenges are looked at, and these ways

**Table 3** Important aspects of objective functions

| Optimizing function | Examples | |
|---|---|---|
| Reduced overall expense [86] | Capital expense | Yearly worth of the system machines startup and growth investments |
| | Operational expense | The administration and service expenses, fuel expenses, transmission expenses |
| | Carbon expense | The overall price of carbon trading, carbon capture and storage |
| | Sustainable power expense | Charge for misuse or storing of sustainable power, including the cost of exchanging clean certificates |
| | Load response expense | Supply–demand cooperation expenses, such as variable load shifting expenses |
| | Integration expense | Costs for recovery, storing, labor, and subsidies |
| Reduce carbon emissions [89] | | Bi-objective optimization framework |
| Optimize the proportion of sustainable energy [93] | | Bi-objective optimization framework |

are put into groups and summed up. In [151], the MATLAB fmincon solver is used to address the combinatorial optimization challenge of optimum planning of IENs for financial and sustainability benefits.

In [70], the Benders decomposition approach is utilized to address the optimization model of the mixed system. The initial optimization issue is split into two parts: the central problem of the heat exchanger and the subproblem of the energy network, each of which is tackled repeatedly. Combinatorial optimization issues frequently employ the Benders decomposition approach. The present implementation of the Benders decomposition method is described, and its practical application is outlined in [152]. Likewise, cognitive approaches have undergone substantial advancements. The Bacterial Community Chemistry (BCC) program is an adaptive optimization technique based on biological behavior that offers global search, rapid settlement, and excellent precision [153].

To solve the problem of nonlinear optimization, many scientists have come up with methods that mimic the way population genetics works, such as genetic schemes, ant colony methods, and particle swarm methods. According to [154], because these algorithms do not need to know the gradient of the optimization problem to solve it, they are perfect for large, hard optimization problems that cannot be solved with traditional methods. Still, due to the number and complexity of design problems, these swarm-based methods will not be able to solve all of them in all situations. To deal with a model that has a complicated structure, a lot of variables, and constraints that do not follow a straight line, these methods need to be improved.

## 5.4 The Cooperative Multi-agent Framework

Multi-energy linkage redundancy and multi-agent game are two essential elements of an IENs. Consequently, the concept of cooperative programming between numerous agents is a significant area of research. Reference [155] analyzed electric synergy networks and economic assumptions for carbon trading are strengthened. The carbon trading-aware scheduling system is developed for electric-powered IENs. In addition to studying electrical synergy networks, the study also considers carbon capture in an attempt to lower carbon emissions from the energy supplier side while implementing carbon trading. The multi-energy interconnectivity system produced by the linking of gas and electricity has garnered a great deal of interest due to its durability and effectiveness. Nevertheless, the function of the natural gas network and the function of the electricity network correspond to distinct time frames, and the functioning of the linking network must account for this aspect. In ref. [156], the dynamic power flow estimate for the natural gas network is determined. To accomplish the optimized distribution of energy hardware capacity, Ref. [157] optimizes the entire optimization architecture of the embedded power microgrid, which includes the CHP production unit, and validates the model's efficacy by correlating study.

## 6 Conclusions and Prospects

The attainment and deployment of sustainable and low-carbon energy infrastructures are of utmost importance in the conservation of energy resources and the mitigation of emissions. Prior research has shown that the existing planning and management frameworks have achieved significant advancements in their endeavors to achieve optimal results. To achieve this goal, many methods are integrated into IENs to successfully tackle economic and environmental issues. These strategies encompass the adoption of clean energy, the development of carbon trading systems, and the usage of other approaches aimed at reducing carbon emissions. The aforementioned study provides valuable insights into these facets, making it a commendable contribution to the field. Its findings are instrumental in assisting policymakers in formulating efficacious strategies to address the prevailing issues pertaining to detrimental emissions generated by integrated energy networks. Moreover, the research findings are of utmost importance in assisting engineers and scientists in the adaptation of traditional power networks into integrated energy networks with the aim of achieving sustainable power. Through the integration of sustainable energy sources, carbon trading mechanisms, and other innovative emission reduction methods, IENs play a pivotal role in facilitating the adoption of environmentally friendly alternatives within the global power infrastructure. This, in turn, enables the attainment of power conservation goals and the reduction of harmful emissions. Despite the advancements achieved in the integration of sustainable energy sources and the implementation of measures to reduce carbon emissions, certain concerns arise in the process of decarbonizing contemporary technology-driven energy systems. The primary objective remains the reduction of overall costs by incorporating carbon emissions and trading costs as manageable variables within the management framework of IENs. In light of the growing uncertainties in supply and demand dynamics, it is imperative to adopt a hybrid energy system management approach and utilize sophisticated modeling tools to effectively assess energy generation and consumption patterns. The recent progress in IENs has been noteworthy; however, additional improvements are necessary in the domains of supply, network infrastructure, demand management, and energy storage to enhance their overall flexibility. The lack of adequate financial resources and limited access to information have posed significant challenges to the widespread adoption of comprehensive systems and methods for optimizing carbon reduction. As a result, there is a need for additional practices informed by research findings in order to achieve low-carbon IENs. In order to enhance operational efficiency, it is imperative for future research endeavors to prioritize the comprehension of the intricate dynamics that arise from the interaction between diverse forms of power flow across varying circumstances. A comprehensive examination of the synergistic progress made in multiple energy technologies and their utilization in diverse decarbonization contexts, encompassing the concept of a market for electricity devoid of carbon emissions, is equally imperative. In closing, it can be argued that IENs offer a feasible approach to attaining sustainable energy production and reducing emissions. However, the existing body of research on the development and operation of low-carbon power systems for future generations is still in its early stages, requiring more improvement and progress. The achievement of a more sustainable energy future through the implementation of IENs may be facilitated by promoting collaboration among politicians, engineers, scientists, and researchers. This collaborative approach can significantly contribute to global efforts aimed at minimizing the impacts of climate change.

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## Declarations

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