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Research Paper

Review of multi-vectored energy hubs: Concept, architecture, management strategies, and research directions

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ABSTRACT

The growing complexity and sectoral interdependence of modern energy systems necessitate transitioning from single-vector operation to an integrated multi-vectored and networked framework. Multi-Vectored Energy Hubs (MVEHs) and their networked extensions (MV-NEHs) present a promising solution for co-optimizing various energy vectors such as electricity, gas, heat, hydrogen, water and other carriers under an integrated structure. The coordinated approach enhances system efficiency, flexibility, and resilience while facilitating efficient renewable energy utilization and reducing emissions. This paper systematically reviews the concept, architecture and management strategies of MVEHs, with a strong emphasis on their operational interaction with power systems under IEEE and other benchmark test cases. The role of game-theoretic, cooperative, and transactive energy management mechanisms in improving networked architectures is explored, alongside advances in flexible technologies such as demand response and Power-to-X for achieving low-emission energy systems. A detailed comparison of test systems, objectives, constraints, solver platforms, and coupling configurations is provided, highlighting how network size and structure influence multi-vector integration. Combining insights from over 230 studies, the review underscores the need to develop benchmark frameworks for multi-energy integration within IEEE-based power systems that reflect operational constraints and enable realistic cross-vector coordination. This necessitates hybrid frameworks combining robust optimization, multi-layer governance, and distributed cooperative–competitive energy management schemes. Emphasis should be placed on aligning operational control and long-term planning across temporal hierarchies and energy vectors through System-of-Systems (SoS) approaches and real-time responsive architectures.

1. Introduction

In traditional power systems, energy distribution networks, such as electricity and gas, have predominantly operated independently, with minimal consideration of their interdependencies. This lack of coordinated energy management between multi-carrier systems leads to inefficiencies, higher operating costs, and suboptimal system performance (McGookin et al., 2021). Furthermore, conventional power systems are centralized and heavily reliant on fossil fuel generation, which contributes to increased operating costs, elevated emissions, and significant energy losses (Chen et al., 2011).

To address these challenges and transition toward sustainable and emission-free energy systems, researchers introduced the concept of microgrids (MGs) integrated with distributed energy resources (DERs) (Espe et al., 2018). MGs are localized electrical networks capable of operating in both grid-connected and islanded modes. They incorporate renewable energy sources (RESs), energy storage units (ESUs), and conventional generation technologies to enhance system reliability and flexibility (Di Somma et al., 2018). Typically located close to load centers, MGs reduce transmission losses while providing economic,

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environmental, and sustainable energy solutions (Uddin et al., 2020). Although RESs are recognized as clean and carbon-neutral technologies, their inherent variability and uncertainty necessitate the development of effective and flexible energy management frameworks (Tiwari and Singh, 2023, 2024). The stochastic nature of renewables poses a risk to the stability and reliability of MGs, making it essential to strike an optimal balance when integrating RESs at scale (Rezaei et al., 2018; Tiwari et al., 2024). Some frameworks propose penalizing RESs for their unpredictable output to encourage a more balanced and robust system design (refs). However, respective frameworks focus on MGs that often operate and are considered as single-carrier electrical networks, which limits their ability to meet diverse electrical and thermal demands and constrains the full exploitation of multi-energy synergies and advanced energy conversion technologies such as Power-to-X.

The demand for electrical and thermal energy has grown significantly in recent years. Advances in combined heat and power (CHP) systems have facilitated the combined utilization of natural gas and electricity, effectively meeting the distribution system's heating and electricity requirements (Shekari et al., 2019). Integrating gas and electricity networks into a unified energy portfolio enhances system reliability and efficiency by enabling power exchange and interaction under both normal and adverse operating conditions (Javadi et al., 2022a). To address the complexities associated with multi-carrier energy systems, the concept of multi-vector energy hubs (MVEHs) has been proposed. These hubs leverage diverse energy sources, including natural gas and electricity from both fossil-based and renewable origins, to optimize energy utilization (Cardoso et al., 2023). MVEHs employ various energy conversion technologies such as CHPs, gas boilers, absorption and electric chillers, electric heat pumps, and power-to-X technologies (e.g., methanization reactors and electrolyzers), as well as fuel cell units, to meet combined electrical and thermal energy demands (Jordehi, 2022).

Multi-vector energy hubs (MVEHs) enhance system performance and flexibility by integrating advanced energy storage technologies such as electric vehicles (EVs), adiabatic compressed air energy storage (A-CAES), hydrogen storage, and pumped hydro storage, alongside traditional electric and thermal storage, improving reliability (Mohsenzadeh et al., 2018). Expanding MVEHs into interconnected networks, termed Multi-Vectored Networked Energy Hubs (MV-NEHs), allows for enhanced controllability and efficiency (Javadi et al., 2022b; Wang et al., 2018a). Advances in energy conversion technologies, including CHP units, electric heat pumps (EHPs), absorption chillers (ACs), and power-to-gas systems, have strengthened interdependence among energy systems, facilitating these coalitions. This interconnected topology enables MVEHs to transact energy or convert it between forms based on demand, fostering flexibility and adaptability and supporting resilience-oriented multi-energy system designs (Hinkelman et al., 2025).

Unlike conventional power systems, MV-NEHs leverage coalition-based frameworks to enable energy transactions within local markets through transactive energy (TE) management (Dabbaghjamanesh et al., 2020). TE, a set of economic and control mechanisms, balances supply and demand dynamically within distributed energy systems while achieving objectives such as reducing operational costs, lowering emissions, and maintaining system security and privacy (Paiho et al., 2021). The cooperative framework allows hubs to exchange energy during emergencies, ensuring collective and individual benefits. In an MV-NEH, hubs with surplus renewable energy can supply it to others during peak demand, or excess energy can be converted into synthetic gas via power-to-gas units, maximizing local RES utilization and reducing curtailment. This strategy minimizes grid dependency, lowers costs, and enhances network self-reliability, fostering a decarbonized and sustainable energy system (Chandra et al., 2021; Ahmadi and Rezaei, 2020).

To further support low-emission models, carbon reduction (CDR) techniques must be integrated into energy hubs. Carbon capture, storage, and utilization (CCS-U) systems offer a practical solution for reducing emissions (Zhang et al., 2022a). However, these systems are energy-intensive, leading to higher operational costs and reduced efficiency (Yang et al., 2022). An emission market mechanism can address these challenges by enabling energy hubs to capture emissions, gain emission rights, and trade these rights in emission markets for profit. Such mechanisms, combined with CCS-U technologies, can transform low-emission energy hubs into economically viable and sustainable models, advancing the MVEH framework. The Road Map for the Evolution of Networked Multi-Vectored Energy Hubs is represented in Fig. 1.

Thus, to develop integrated, sustainable, and resilient energy systems, it is essential to implement effective co-energy management strategies tailored for interconnected multi-energy systems. These strategies should emphasize the optimization of resource utilization, enhancement of operational flexibility, and reinforcement of system resilience to meet the increasing energy demands of modern society.

In recent years, several review studies have examined different dimensions of multi-energy systems, including modelling frameworks, control and optimization strategies, flexibility assessment, and the integration of emerging low-emission and conversion technologies. Reference (Mokaramian et al., 2025) provided an informative analysis on energy hubs with a focus on flexibility, energy storage, demand response strategies and optimization techniques. A descriptive classification of energy hub models, their definitions and their practical use case applications are presented in Eladl et al. (2023). Study highlights that the first kind of EH is modelled to integrate bioenergy with electrical and natural gas systems to meet heating and electrical demand. Further, studies (Hinkelman et al., 2025; Paiho et al., 2021; Ding et al., 2022) and (Jasinski et al., 2023) reviewed optimization and control algorithms to optimally operationalize the multi-energy hubs for trading and dispatch and focused on uncertainty modelling using stochastic and robust approaches.

Although the current literature has contributed to the modelling of multi-energy systems, most studies primarily focus on optimization strategies, flexibility enhancement, and uncertainty analysis, often addressing these aspects in isolation, without explicitly examining their interaction and representation within power-system (IEEE) benchmark frameworks. Moreover, a comprehensive evaluation of coordinated architectures and advanced energy management approaches, including new advances on cooperative, transactive, and game-theoretic schemes, critical for developing robust and scalable multi-vectored networked energy hubs (MV-NEHs), has not been systematically reviewed.

With the aforementioned literature, this review provides a comprehensive power-system-oriented research perspective on multi-vectored and networked energy hubs, with the key objectives and contributions highlighted in the subsequent section.

1.1. Objectives and key contributions

The primary objective of this paper is to provide a comprehensive review of the evolution of multi-vector energy hubs (MVEHs) and their networked extensions (MV-NEHs), with a focus on core architectural designs, advanced energy management strategies, including transactive and game-theoretic coordination, while, critically highlighting their representation and evaluation within IEEE-based power system testbeds, and the associated risks and uncertainties that affects operational conditions of the integrated system. The review aims to identify key methodological gaps and outline future directions for modelling robust, efficient, and low-emission multi-energy systems.

In this context, the paper analyses architectural and coordination frameworks that enable optimal interaction of individual energy hubs to form networked systems (MV-NEHs), enhancing system flexibility, resource utilization, and economic and environmental efficiency. The particular focus is given to transactive energy-based cooperative management strategies, distributed and system of systems (SoS)

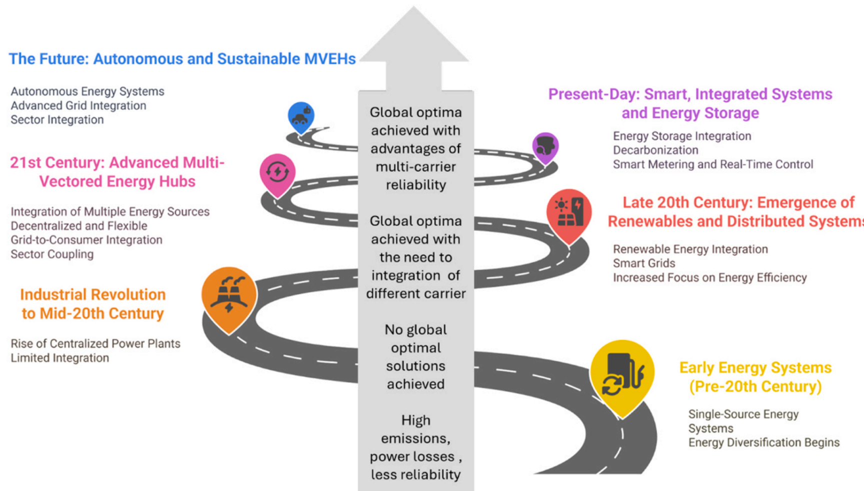

Fig. 1. Road Map for the Evolution of Networked Multi-Vectored Energy Hubs.

architecture, and emerging Power-to-X pathways and their representation within IEEE bus networks. The study also examines multi-domain uncertainty and risk- prevalent to MV-NEHs, addressing renewable variability, multi-carrier dependencies, and operational complexity. The key contributions of this study are as follows:

- A systematic classification of MVEH/MV-NEH architectural designs and different energy management strategies with a special focus on a cooperative game mechanism that allows different participating players in network architecture to achieve both system-wide objectives and individual ensuring individual economic goals.
- Assessment on integration of low-emission and flexible technologies, such as Power-to-X, CCS-U, and advanced storage, within multi-energy systems, and assessment of associated risk and uncertainties.
- Mapping and representation of multi-energy hub concepts to IEEE test systems, review on development of optimization models for multi-energy distribution systems and highlighting the most widely adopted framework.
- Finally, identifying the key research gaps and future research directions in a tabular way, offering a systematic perspective on the evolving landscape of multi-energy systems and their management under dynamic and uncertain operating conditions.

The rest of the paper is structured as follows: Section 2 presents the methodology of the paper. Section 3 introduces the concept of multi-vectored energy systems, while Section 4 explores the architecture for managing the networked energy hubs. Section 5 delves into energy management strategies within the networked framework, highlighting recent advancements in these areas. Section 6 examines the evolution of low-emission systems, emphasizing the integration of advanced technologies such as power-to-X, carbon capture and hydrogen. Section 7 highlights the development of IEEE systems to support the effective integration of multi-energy systems. Further, Section 8 presents the uncertainties and risks involved in energy hubs. Finally, Section 9 identifies key research gaps and proposes future directions to address these challenges. The study concludes by summarizing the findings and discussing their implications for the advancement of sustainable and resilient energy systems. To improve readability, each major section, especially Sections 3–6, is concluded with a 'Recent Research Developments' sub-section, summarising the relevant latest literature.

2. Research methodology

According to a recent estimate by the US Department of Energy (DOE), networked energy systems could power up to 13,000 MW of loads by 2020 (Marnay et al., 2015). Recently, a lot of focus has been given to the energy hub modelling. Fig. 2 displays the number of Scopus-indexed journal papers having the keyword “Multi-energy system”. It can be noticed that there is a sharp increase in the published papers from 2017 (Eladl et al., 2023; Karimi and Jadid, 2020). Recent research articles have explored several aspects of network systems, such as reliability (Farzin et al., 2018), energy management (Choobineh and Mohagheghi, 2018), and more. Fig. 3 shows the pioneering countries in the multi-energy systems. According to the Scopus database, 862 papers were published by China. Italy and the United Kingdom are the next ranks with 180 and 149 papers, respectively. Also, most of the published papers were focused on energy and engineering by 29 %. Computer science with 11 % and environmental science with 8 % are the next (Fig. 4). The idea of multi-vectored energy hubs and network topology can result in a coalition of numerous multi-vectored energy hubs to model a reliable and sustainable energy system, as shown in Fig. 5.

To ensure a comprehensive and transparent assessment of the evolution of multi-vectored energy hubs (MVEHs), this study adopts a systematic literature review approach inspired by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The review process focused on identifying, screening, and analyzing relevant studies to determine the current state of energy management strategies in multi-carrier systems. The literature search was conducted using the SCOPUS database, chosen for its extensive coverage of energy-related publications. The search was conducted using keywords that include “multi-energy hubs”, “multi-vectored”, “energy hubs”, “integrated energy systems”, “multi-energy hubs with uncertainty” and “power-to-X systems”, and “low emission multi-vectored energy hub”. To ensure the relevance and currency of the review, the following inclusion criteria were applied: (i) Publications from 2010 to 2025 were selected to capture recent technological advancements and research directions. (ii) Articles were required to focus specifically on the architecture, reliability, or energy management of MVEHs. (iii) Only peer-reviewed journal articles and conference proceedings written in English were considered. As illustrated in Fig. 6, the initial search yielded 862 papers. A filtration process was then conducted to remove duplicates and screen titles/abstracts for relevance. Studies that did not provide a comprehensive analysis or fell outside the scope of multi-vectored systems were excluded. Following this screening process, approximately 230 studies were selected for the final extraction and critical review.

3. Multi-vectored energy hub concept

Physically, energy systems are intrinsically "multi-energy" by nature,

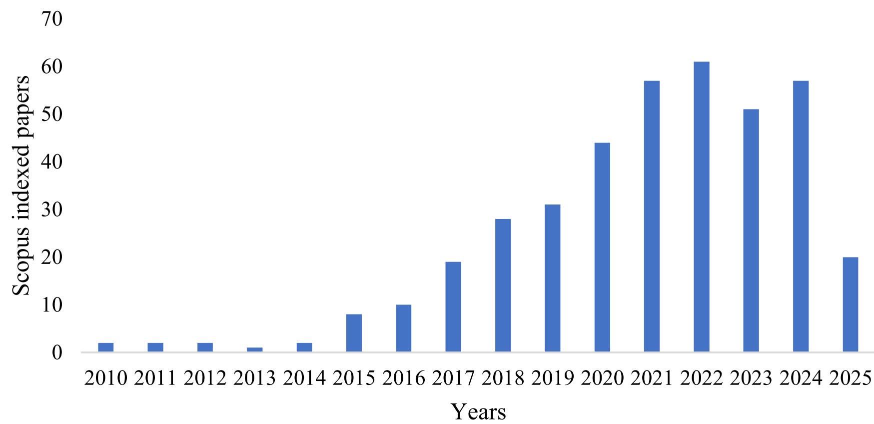

Fig. 2. Recent Scopus indexed journal publications.

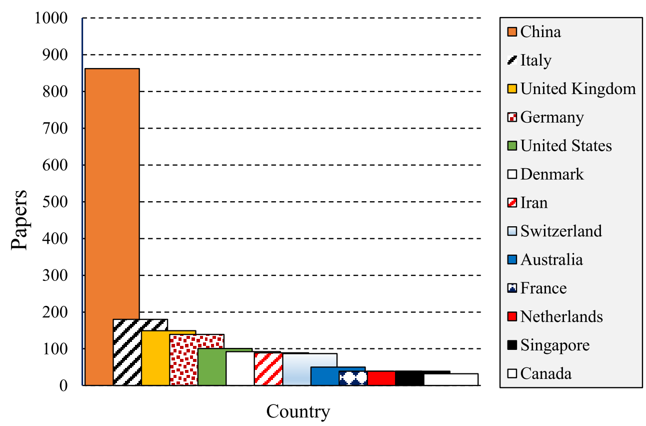

Fig. 3. Pioneering countries in multi-energy systems.

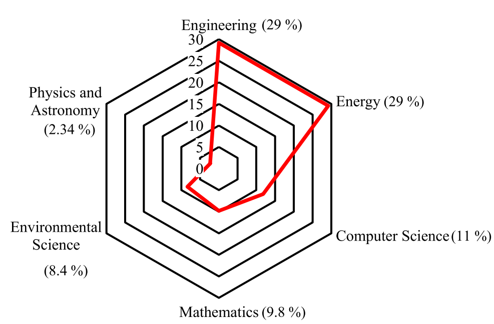

Fig. 4. Subject areas in multi-energy systems.

as various energy vectors and sectors interact across multiple layers, interconnected through networks. However, within the context of this research, the term "multi-energy" is specifically defined to reflect a holistic approach aimed at optimizing and evaluating energy systems within a specific region characterized by both electrical and thermal load demands. This perspective emphasizes integrated resource management to ensure efficiency, sustainability, and system-wide reliability (Mancarella, 2014). This approach allows for the integration of the multi-sectors, allowing the framework to facilitate the positive properties such as flexibility and reliability, which are normally studied and analyzed separately (Zamora and Srivastava, 2018). This approach provides a novel perspective on energy system analysis, particularly by emphasizing the reduction of the environmental footprint of energy services. Simultaneously, it incorporates economic and reliability constraints, ensuring that system performance aligns with sustainability goals without compromising cost-effectiveness or operational stability. In fact, using a multi-vectored energy hub system (MVEH) approach provides several advantages, including:

- Improving conversion rates and operation of primary energy sources, for example, through the use of Distributed Multi-Generation (DMG) technologies.
- Facilitating the optimal system-level integration and deployment of centralized and decentralized resources requires efficient market interactions. For instance, in energy systems dominated by wind power, small-scale heat-buffered Combined Heat and Power (CHP) systems can play a pivotal role by dynamically responding to fluctuations in electricity market prices. This adaptability not only supports grid stability but also enhances the economic viability of decentralized resources by leveraging market-driven opportunities.
- Increasing the energy system's flexibility. This can be accomplished by allowing electrically powered thermal loads or gas-powered electrical loads, such as CHPs and Electric Heat Pumps (EHPs), which could provide the backup at the time of critical conditions, such as peaks or system congestion. EHPs could even provide the ancillary support by reducing their demands during peak loads. Furthermore, the Electric Vehicles (EVs) could similarly support the system (Son et al., 2021).

Overall, a multi-vectored energy hub (MVEH) approach allows for a thorough analysis of energy systems, taking into account various factors such as efficiency, optimal resource deployment, and system flexibility, to reduce environmental burdens while meeting economic and reliability requirements.

Multi-vectored energy hubs combine different types of energy-generating sources and generate energy for electrical and thermal demands in the presence of multiple energy storage units and energy conversion units. Most commonly, an energy hub considers electrical-heat (Mirzaei et al., 2020) or electrical-heat-ice systems (Heidari et al., 2020). Further, with the recent developments in hydrogen systems and power-to-gas units, electrical-heat-ice-hydrogen (Rezaei and Pezhmani, 2022) integrated energy hubs are modelled. Usually, the operation of electricity and gas networks was considered independently; however, the inherent interconnection between these networks significantly influences their performance and operation. The increasing integration of electricity and gas (heat) networks is driven by the growing deployment of gas-fired combined heat and power (CHP) units, electrical heat pumps, absorption and electric chillers technologies. This integration enhances the operational synergy of these networks, addressing contemporary energy challenges. The typical architecture of an energy hub is shown in Fig. 7. The key idea is to integrate different inputs and analyze how different inputs interact with each other through different technologies to produce a resilient, holistic energy system. The

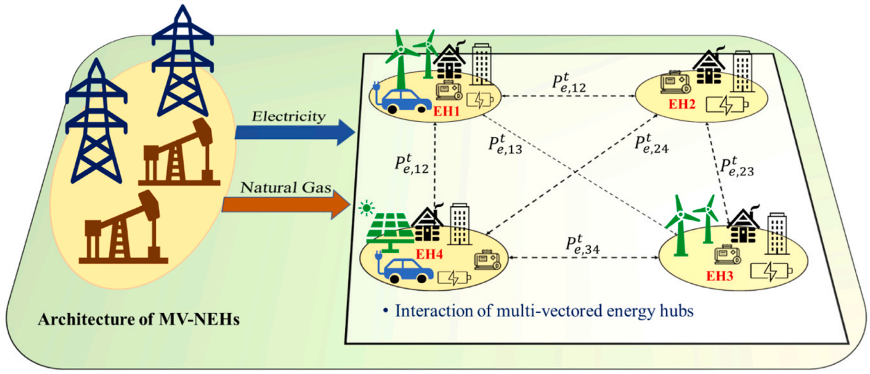

Fig. 5. Structure of interconnected multi-vectored energy hubs.

systematic mathematical representation of the energy hub is highlighted in (1). A typical example of an integrated electrical-heat-ice multi-energy framework is highlighted in Fig. 8, along with different energy conversion technologies. A robust MVEH should be integrated with different storage to store the necessary energy to be used during the peaks for each vector.

$$\begin{bmatrix} P_e(t) \\ P_g(t) \\ \vdots \\ P_m(t) \end{bmatrix}^T \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1n} \\ C_{21} & C_{22} & \cdots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m1} & C_{m2} & \cdots & C_{mn} \end{bmatrix} = \begin{bmatrix} L_e(t) \\ L_g(t) \\ \vdots \\ L_n(t) \end{bmatrix}^T \quad (1)$$

Eq. (1) provides a generic matrix-based formulation of energy flow balance in a multi-vector energy hub (MVEH). It captures how diverse input carriers, such as electricity $P_e(t)$, gas $P_g(t)$ or other vectors $P_m(t)$, are transformed through conversion pathways into corresponding loads $L_e(t)$, $L_g(t)$, $L_n(t)$ via a coupling matrix $[C_{mn}]$, where (t) highlights their variation with time. This abstract structure generalizes the role of internal technologies such as CHP units, heat pumps, electrolyzers, and storage devices. While not a full operational model, Eq. (1) serves as a foundational representation of energy coupling, enabling the structural interpretation of control, coordination, and uncertainty approaches analyzed in this review.

Gas-fired generation plants provide distinct advantages over conventional thermal plants, including lower costs, reduced emissions, and rapid response to renewable energy fluctuations, making them well-suited for systems with high renewable penetration. For instance, according to the U.S. Energy Information Administration (EIA) (EIA, 2024), natural gas reached about 43 % of U.S. utility-scale electricity generation in 2023, while global consumption increased from approximately 1500 billion cubic meters (bcm) in 2015–2016 to over 1750 bcm in 2025 (IEA, 2020) in power production, demonstrating the growing importance of integrated gas and electricity networks in enhancing efficiency and sustainability (Alabdulwahab et al., 2015). Cogeneration systems, particularly CHP plants, are essential in integrated energy frameworks for industrial, commercial, and residential sectors. These systems, coupled with district heating networks (DHNs), achieve efficiencies of up to 90 % while reducing emissions by 13–18 % (Wang et al., 2018b; Comodi et al., 2017; Nazari-Heris et al., 2019).

Beyond CHPs, multi-vectored energy hubs (MVEHs) incorporate advanced technologies such as electric heat pumps (EHPs), absorption chillers (ACs), gas boilers (GBs), power-to-X systems, and fuel cells (FCs) to co-generate electricity and heat, meeting diverse energy demands with improved flexibility (Gu et al., 2014). Renewable energy integration, particularly photovoltaic (PV) systems, further strengthens MVEHs, addressing environmental concerns while enhancing sustainability (Zhang et al., 2014; Rehmani et al., 2018). To address capacity constraints, energy sharing among microgrids (MGs) has been proposed, reducing costs and improving reliability (Fathi and Bevrani, 2013). Heat-electricity integrated multi-vector systems connecting multiple MGs with CHP and PV systems optimize energy use and system performance (Shao et al., 2018; Massrur et al., 2018).

The primary operational goals of CHP-based microgrids include minimizing costs, maximizing efficiency, and reducing environmental impact (Aluisio et al., 2017; Zhang et al., 2015). Research (Wang et al., 2017) introduces schemes to optimize energy and backup capacity in CCHP-based MGs. Studies such as (Aluisio et al., 2017) and (Nikmehr and Najafi-Ravadanegh, 2015) focus on minimizing costs and emissions while ensuring optimal day-ahead operation in microgrids. These developments underscore the importance of integrated energy management strategies for sustainable, cost-effective, and resilient energy systems.

3.1. Recent research developments

Recent studies have increasingly concentrated on optimal energy management within multi-energy systems, operating either autonomously or in a coordinated mode. This focus includes the integration of advanced energy storage technologies and energy conversion units. Optimization strategies for scheduling integrated heat, electricity, and cooling systems under solar irradiance uncertainties have been widely studied in Javadi et al. (2019), while a chance-constrained problem formulation is discussed (Javadi et al., 2020). In Jafari et al. (2020), a tri-objective problem formulation is modelled to minimize the operating cost, energy not supplied ENS), and emissions for an electrical (single-carrier) microgrid. A stochastic genetic algorithm-based model for multi-vector systems (heat-ice-electricity) in (Noorollahi et al. (2022) analyses the effects of heat pumps, absorption chillers, and heat storage on costs but excludes demand response and flexible resources. Study (Dong et al., 2020) proposes the concept of virtual power plants and formulates a stochastic, single-objective formulation to analyze the coordinated operation of wind, solar, and pumped hydro storage for minimizing net operational costs. A resilience analysis for a multi-energy single microgrid is explored in Rahgozar et al. (2022), addressing uncertainties in RES and equipment outages alongside electrical demand response and storage systems for electrical, heat, and cold energy. However, this study does not consider the networked structure or the role of flexible technologies such as pumped hydro storage, electric vehicles, and demand response for heat and cold. Reference (Monemi Bidgoli et al., 2021) develops a stochastic, multi-objective problem formulation for a single multi-energy microgrid, targeting the minimization of cost, power loss, emissions, and reserve capacity utilization, with several formulations implicitly or explicitly adopting multi-timescale coordinated control across day-ahead (DA), intraday (ID), and real-time (RT) operation.

Despite the extensive work discussed in the previous sections, most formulations concentrate on single-hub or single-carrier configurations and only partially address coordinated networked operation at the multi-vector level (Javadi et al., 2020; Jafari et al., 2020; Noorollahi

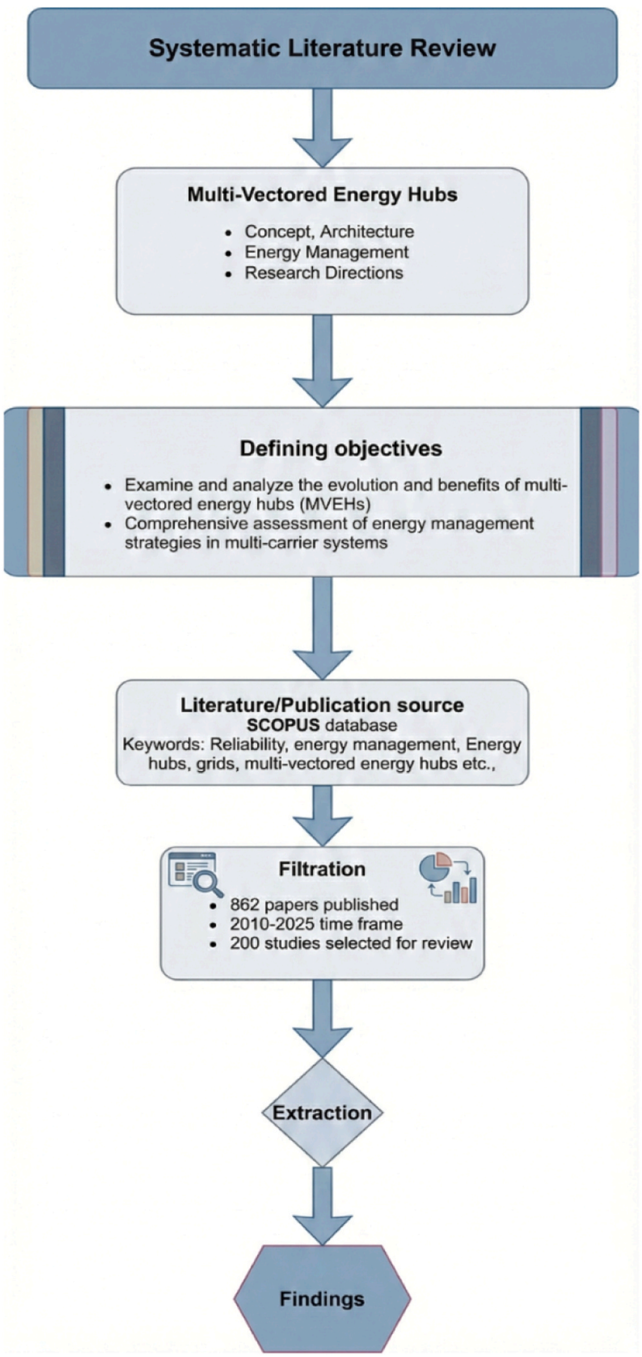

Fig. 6. Research methodology of the proposed study.

et al., 2022; Dong et al., 2020; Rahgozar et al., 2022; Monemi Bidgoli et al., 2021). In particular, several studies provide detailed models for individual microgrids or energy hubs, while the explicit representation of multi-hub coordination, community-level flexibility services, and system-wide risk propagation under RES uncertainty remains comparatively less explored. Thus, energy management schemes should incentivize emission-free generation while penalizing stochasticity in RES performance to ensure a balanced and resilient energy system.

Moreover, in Cai et al. (2020) and Daneshvar et al. (2020)a, the authors discuss the robust model predictive control (MPC) optimization for energy management of MG the under RES uncertainty. However, similar to the studies (Javadi et al., 2020; Jafari et al., 2020; Noorollahi et al., 2022; Dong et al., 2020; Rahgozar et al., 2022; Monemi Bidgoli et al., 2021), this study is limited to single energy system MG

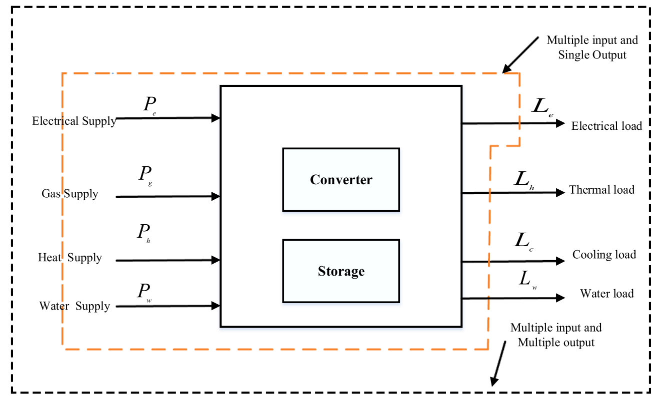

Fig. 7. Generalized framework representing interaction of multiple energy carriers.

consideration, while the battery vehicles and flexible demand management are not being explored to ensure the flexible system. The prominent challenges in the single carrier microgrid system include generation capacity, integration of energy storage & grid stability, etc. Some research studies focus on the multi-vector system to overcome the above challenges. Research (Eladl et al., 2020) incorporates tri-level optimization, neglecting the integration of flexibility technologies. In El-Zonkoly (2017), the optimal operation of multi-carrier EHs is analyzed by incorporating heat and compressed air battery storage systems while considering technical constraints of the network. Ref (Shams et al., 2019). develops a scenario-based uncertainty handling algorithm for optimal planning and operation of multi-vector energy hubs MVEHs), although it does not address battery electric vehicle (BEV) uncertainties or demand response. In (Najafi et al. (2021), the stochastic energy scheduling for vectored energy systems is proposed using a chance-constrained approach. Study (Hou et al., 2020) proposes a stochastic optimization framework for multi-vector energy hub systems, integrating electrical and heat systems with flexibility considerations. Similarly, research (Mirzapour-Kamanaj et al., 2020) discusses the optimal management of MVEHs considering RES uncertainties. However, these findings ignore the impact of electric vehicle integration and demand response on system flexibility. Assessment on the demand-side management and flexibility while addressing the RES uncertainties is highlighted in Wu et al. (2018); Faraji et al. (2021). However, the literature (Cai et al., 2020; Daneshvar et al., 2020a; Eladl et al., 2020; El-Zonkoly, 2017; Shams et al., 2019; Najafi et al., 2021; Hou et al., 2020; Mirzapour-Kamanaj et al., 2020; Wu et al., 2018; Faraji et al., 2021) does not assess the integration of EVs with a multi-vectored networked framework, which is critical for assessing the environmental and economic impacts of such systems.

To enable flexible and cost-effective operations, multi-energy hubs integrate various flexible technologies. Electric vehicles (EVs) play a critical role in ensuring flexibility and supporting energy hubs during peak demand. With increasing EV market penetration, their potential to reduce costs and emissions in microgrids has gained significant attention. Study (Lekvan et al., 2021) explores robust optimization for microgrids with RESs, battery storage, and flexible technologies like EVs while addressing RES uncertainties. However, advanced storage options such as compressed air, pumped hydro, and cooling loads are not considered.

Emission-based optimization integrating EVs, heat, and electrical storage is discussed in Luo et al. (2020), while (Dabbaghjamanesh et al., 2021) employs deep learning to address BEV stochasticity in MVEHs. Although (Lekvan et al., 2021; Luo et al., 2020; Dabbaghjamanesh et al., 2021) integrated EVs in microgrid operations, they do not fully address RES uncertainties and the multi-vector aspect. Reference (Nosratabadi et al., 2021) investigates stochastic planning of diverse energy storage systems (electrical, heat, ice, hydrogen), including demand response and

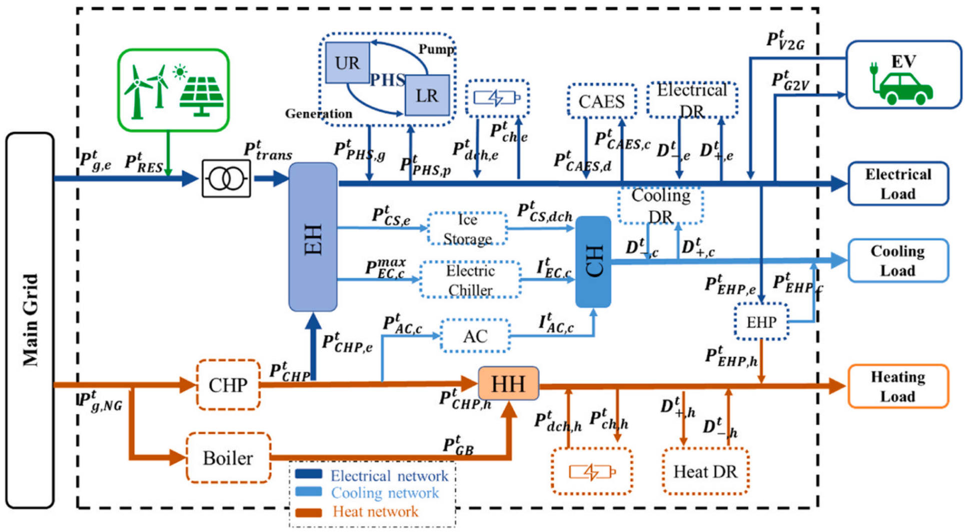

Fig. 8. Interconnections and energy flow in a typical energy hub.

CHPs, but overlooks RES curtailment, GHG impacts, and multi-energy hub cooperation. Similarly, (Li et al., 2018) focuses on emission-based optimization with EVs and storage but lacks consideration of networked energy hubs.

References (Rezaei and Pezhmani, 2022; Alabdulwahab et al., 2015; Wang et al., 2018b; Comodi et al., 2017; Nazari-Heris et al., 2019; Gu et al., 2014; Zhang et al., 2014; Rehmani et al., 2018; Fathi and Bevrani, 2013; Shao et al., 2018; Massrur et al., 2018; Aluisio et al., 2017; Zhang et al., 2015; Wang et al., 2017; Nikmehr and Najafi-Ravadanegh, 2015; Javadi et al., 2019, 2020; Jafari et al., 2020; Noorollahi et al., 2022; Dong et al., 2020; Rahgozar et al., 2022; Monemi Bidgoli et al., 2021; Cai et al., 2020; Daneshvar et al., 2020a; Eladl et al., 2020; El-Zonkoly, 2017; Shams et al., 2019; Najafi et al., 2021; Hou et al., 2020; Mirzapour-Kamanaj et al., 2020; Wu et al., 2018; Faraji et al., 2021) also limit their scope to single multi-vector hubs without addressing cluster or network formations and EV integration in energy management. The optimization of multiple energy conversion technologies across an interconnected networked system remains a challenge. This approach is essential for reducing regional costs while maintaining the individual hub and regional interests. Although EVs' flexibility in multi-vector systems is analyzed in (Lekvan et al., 2021; Luo et al., 2020; Dabbaghjamanesh et al., 2021; Nosratabadi et al., 2021; Li et al., 2018), aspects such as network topology, advanced storage integration, and multi-energy demand management are not explored in the discussed research studies.

4. Network energy hub concept

The concept of multi-vectored energy hubs (MVEHs) can be extended to the regional scale, where multiple interconnected systems interact to provide a comprehensive regional energy solution. Inspired by the multi-microgrid (MMG) concept, these networked energy hubs enable energy exchange during periods of surplus or shortage, reducing reliance on the main grid and enhancing system resilience and flexibility (Dabbaghjamanesh et al., 2020). The coalition of these MVEHs at the regional level forms what is termed Multi-Vectored Networked Energy Hubs (MV-NEHs). To enhance the flexibility and performance of this topological structure, the integration of advanced technologies such as demand response programs (DRPs), electric vehicles (EVs), and advanced energy storage units (ESUs) is essential (Arnett et al., 2018). To model these aspects under a single framework, an efficient energy management program is essential to enable optimal cooperation within the multi-vectored system, achieving global objectives of MV-NEHs such as regional cost minimization, GHG emission reduction, and improved reliability, while also satisfying individual MVEH goals like profit maximization based on their unique capabilities. In a networked framework, energy hubs can exchange surplus energy and advanced technologies during critical periods, reducing green energy spillage. This coalition-based approach enhances the reliability and overall performance of the system (Saleh et al., 2016).

Nevertheless, the network system or multi-microgrid concept facilitates different energy hubs to collate and exchange energy, and develop a reliable and greener energy system. Further, the cluster formation allows energy hubs to interact with each other in different and new local energy markets, which ensures the potential individual interest of energy hubs. Fig. 5 highlights the graphical representation of four different energy hubs that are connected and also attached to the central grid. Here, each energy hub has different kinds of generating sources, and OECT refers to other energy conversion technologies.

4.1. Network energy hub architecture

The management and control of network microgrids or energy hubs depend on the architecture of the network. The control of the network system can be centralized (Mao et al., 2017), decentralized or distributed (Kou et al., 2017). Further advances in supervisory planning are also prevalent in the literature, such as the system of systems (Zhao et al., 2018). The brief discussion on different architectural schemes is highlighted below, and the graphical representation of each design is highlighted in Fig. 9, adopted from Bandeiras et al. (2020).

4.1.1. Centralized scheme

In this scheme, supervision is managed by a central authority, and no communication has been established between the energy hubs. Fig. 9(a) illustrates the centralized control approach, where a single central controller is responsible for determining the control actions of all local microcontrollers (MCs) and local controllers (LCs) within the system. By collecting and processing data from the local units, the central controller optimizes the overall system operation. Consequently, it governs and coordinates the operation of each microgrid (MG) system within the cluster. Due to the reliance on a single central controller, this approach is straightforward to implement and offers simplicity in its design and deployment (Mao et al., 2017). A cooperation-based centralized energy management scheme is discussed in Song et al. (2015) for networked microgrids.

4.1.2. Decentralized scheme

A decentralized scheme allows the individual operation and

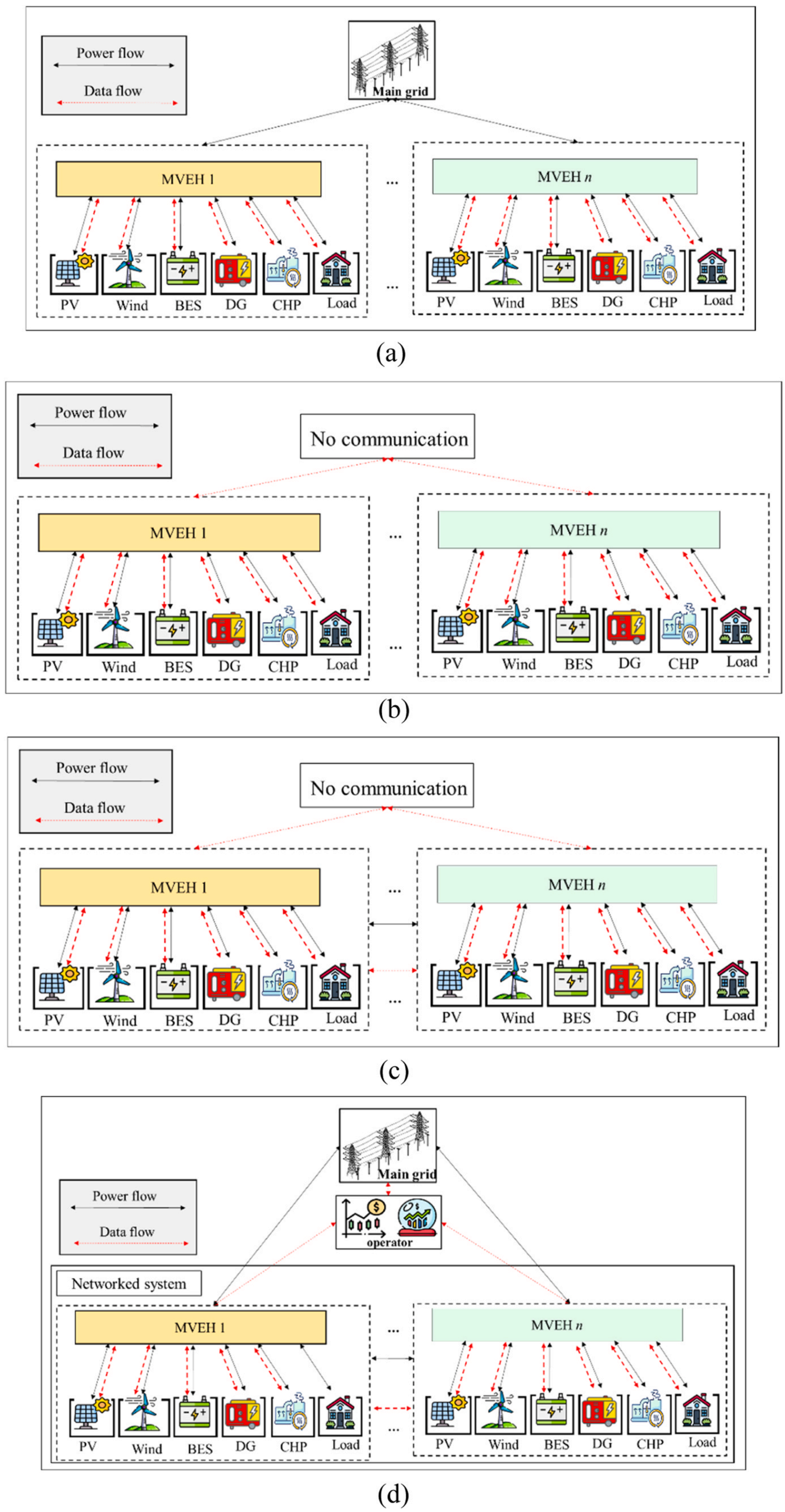

Fig. 9. Different architectures to represent network of energy hubs (a) Centralised (b) Decentralised (c) Distributed (d) System of System Scheme.

management of each microgrid in the network, as shown in Fig. 9(b), rather than depending on inter-microgrid communication. Local energy hub controllers acted autonomously to coordinate the optimal operation of the energy hubs inside a cluster. This decentralized strategy gives individual units autonomy and stability, ensuring robustness in the face of communication breakdowns (Kou et al., 2017). A decentralized control system also makes it simple to scale up in size and complexity. However, this method cannot ensure the cluster's ideal performance because there are no communication links between the MGs. Moreover, the intensified competitiveness among individual units may compromise the overall performance of the cluster. In Wang et al. (2016), a decentralized energy management scheme is presented for single energy source networked microgrids. Each microgrid has its own individual goal, and the scheme facilitates achieving that rather than achieving the cluster targets.

4.1.3. Distributed scheme

In this scheme, microgrids communicate with each other through their individual central controller, as highlighted in Fig. 9c). Here, information is gathered locally and exchanged with the nearby energy hub through individual local controllers. Thus, it removes the issue of local competitiveness in the network. Thus, in this scheme, the network's common goals can be achieved in addition to the optimal management of energy hubs. However, sharing the information may result in security issues. A distributed controlling algorithm, supported by convex optimization, alternating direction method of multipliers (ADMM), is employed in (Liu et al. (2018)a to optimize the energy cost of the multi-microgrid system. Research facilitates each microgrid to forecast the load and generation separately to ensure a secure system. Such architectures are particularly suitable for implementing robust/distributed game-theoretic coordination among hubs, mainly focusing on attaining individual gains.

4.1.4. System of systems

The concept of a system of systems (SoS), as depicted in Fig. 9(d), involves the connection and coordination of diverse autonomous energy systems to create a larger system capable of achieving a collective goal that cannot be accomplished by a single system or a group of uncoordinated systems. In the context of a multi-vectored networked energy hubs (MV-NEH) system, the participating energy hubs are autonomous systems capable of independent operation and management. Each MVEH possesses certain features and attributes, such as excess renewable generation, that could benefit other EHs in the same area at different times. Consequently, by forming the multiple EHs into a grid-connected MV-NEH system and appropriately coordinating their operations, new and advantageous features can emerge (Zhao et al., 2018). These SoS arrangements also provide a natural structural layer for multi-timescale coordinated control, where local hub decisions are aligned with upper-level network objectives.

4.2. Recent research developments

Authors in Anastasiadis et al. (2010) study microgrid network formation for low- and medium-voltage systems under dynamic electricity prices and demonstrate reductions in energy cost, emissions, and transmission losses. These results are obtained within a single-carrier electricity framework, and the extension of such networked strategies to fully coupled heat–power multi-carrier systems remains an open direction for future work. Reference (Nunna and Doolla, 2012) develops multi-microgrid energy management with energy exchange and demand response, while (Nikmehr et al., 2017) analyzes demand response programs for networked MGs with different RESs and shows the advantage of networked operation over conventional schemes. These contributions focus on electrical networks; explicit modelling of integrated heat–-power flows is not the central objective in these studies.

To address the integration of interconnected multi-carrier energy hubs, various studies have explored energy management strategies. A tri-level optimization model in Misaghian et al. (2018) considers multi-vector systems and RES uncertainties but excludes flexible resources. In Hemmati et al. (2020), optimal operations of interconnected hubs with AC power flow constraints and heat-electric BES systems are proposed, though RES curtailment and flexibility remain unaddressed. A two-stage stochastic model in (Mansouri et al., 2020) employs Benders Decomposition for EH scheduling, considering RES uncertainties and electrical DR but excluding EVs, thermal DR, and vehicle-to-grid operations. Similarly, (Nikzad and Samimi, 2021) uses bi-level stochastic optimization with particle swarm algorithms to enhance social welfare via energy storage and DR, but focuses solely on electrical flexibility, neglecting heat distribution networks. While (Hemmati et al., 2020; Mansouri et al., 2020; Nikzad and Samimi, 2021) explore EH energy management under uncertainties, they overlook energy exchange, DR impacts, and EV-related economic and environmental considerations. In (An et al., 2018), a double auction scheme for scheduling networked microgrids (NMG) is proposed. In (Rezaei et al., 2022), risk risk-constrained stochastic optimization framework is developed for NMG. The research formulates a heat-electrical system but ignores the investigation of the cooling system and flexible resources. Robust optimization is applied at the MG level. At the MMG level, energy balance across the MGs is the key objective. Robust optimization is proposed in (Poursmaeil et al., 2021) for heat-electricity integrated EHs while considering flexible demand profiles and EVs. However, the electric vehicle model developed in the paper is very primitive and does not include driving patterns and trip signals.

In comparison to all the architectures discussed in Section 4, the system of systems has the ability to provide the advantages of both centralized supervision and distributed and decentralized management schemes. System of systems architecture solves the issue of security, and it has a central controlling agency for the network. Further, it provides decentralized controlling features as it provides the right to an energy hub to join the network. Thus, the SoS scheme ensures to achieve both global network objectives while guaranteeing to fulfil each participant's individual goals. Hence, this study formulates the SoS approach for modelling the network energy hubs.

Mentioned literature (Mao et al., 2017; Kou et al., 2017; Zhao et al., 2018; Song et al., 2015; Wang et al., 2016; Liu et al., 2018a) and (Anastasiadis et al., 2010; Nunna and Doolla, 2012; Nikmehr et al., 2017) discuss the networked architecture, considering only electrical systems and ignoring the multi-energy architecture in their study. Studies (Arnett et al., 2018; Saleh et al., 2016; Misaghian et al., 2018; Hemmati et al., 2020; Mansouri et al., 2020; Nikzad and Samimi, 2021; An et al., 2018; Rezaei et al., 2022; Poursmaeil et al., 2021) investigate on NMG system and majorly focus on ensuring common interest, while the cooperative framework of microgrids or EHs, ensuring both common as well as individual interest, is not evaluated. Additionally, the reviewed literature overlooks fair payoff allocation mechanisms for distributing profits from optimal scheduling energy management in a networked framework.

5. Energy management schemes

Energy management of a networked multi-energy system is a critical topic due to its complex architecture. With the advancements in energy conversion units, the multi-vectored networked system becomes more interlinked; thus, an efficient energy management scheme must be developed to ensure reliable operation. According to current research, interconnecting or energy hubs as a networked structure increases system performance and reliability, allowing users to benefit from the key advantages of an interconnected multi-vector system (Li et al., 2019). However, it also introduces complexity in optimally controlling the integrated systems; thus, it is important to review the different energy management strategies.

5.1. Energy management strategies in networked systems

Energy management in multi-vector networked energy systems can be addressed through competitive, cooperative, and transactive approaches, implemented across various architectures discussed in the previous section (Bandeiras et al., 2020). Further, this study places particular emphasis on cooperative and transactive energy management schemes, examining their importance for multi-energy systems, and how individual participants within the networked system achieve their own economic objectives while ensuring overall system-wide goals.

5.1.1. Non-cooperative management

Non-cooperative management involves participants who lack a common interest, often due to differences or conflicts among them. In such scenarios, players are unable to establish binding agreements to facilitate interaction. Non-cooperative games typically arise when participants have no prior relationships or interdependencies. Players engaged in competitive games generally have no shared interest in forming coalitions or alliances. However, this does not preclude the possibility of coalition formation; it merely indicates the absence of any prior relationships or shared objectives that could motivate collaboration. In non-cooperative games, participants usually possess comprehensive and detailed strategic information, including knowledge of each other's strategies, timings, and actions (Saad et al., 2012). Players within a region typically adhere to their initial strategies, prioritizing individual economic outcomes over collective regional benefits. The outcomes of non-cooperative games are represented by Nash Equilibrium Points (NEPs), which provide stable solutions but do not necessarily ensure the most economical outcomes (Hamidi et al., 2016). This represents a distributed gaming framework, but is mainly confined to short-term operational horizons without explicit coupling to expansion planning.

The study in Chen and Zhu (2017) utilizes a non-cooperative game theory to evaluate multi-microgrid system operations. In this framework, the players, represented by the microgrids, integrate renewable energy sources (RESs) without accounting for their uncertainties or the implementation of demand response programs. The system's solution is achieved by attaining the Nash Equilibrium.

In Liu et al. (2018)a, a distributed framework is designed to ensure the efficient trading among microgrids using a competitive game approach. Here, each microgrid has multiple individual targets; thus, a competitive approach is best as it will be difficult to bind them in a common agreement. The study in (Xie et al., 2018) presents a competition-based optimization model for MGs and the distribution network, incorporating technical constraints and energy storage systems but excluding demand response and multi-energy systems. In (Jalali et al., 2017), a bilevel multi-follower model optimizes multi-microgrid networks but omits multi-energy system integration and ESSs. Similarly, (Nasiri et al., 2020) proposes a stochastic bi-level multi-carrier framework considering RES uncertainties and MG-central company interactions, but overlooks EVs, thermal and electrical demand, and energy exchange between hubs.

In Salehi et al. (2019), the heat-electricity integrated multi-microgrid framework is investigated along with EVs and DR. An information gap-based stochastic optimization framework is developed in Zare Oskouei et al. (2021) for a heat-electricity integrated networked system. Studies (Salehi et al., 2019; Zare Oskouei et al., 2021) do not explore the independence of energy hubs (EHs), the penalties associated with renewable energy source (RES) curtailment, or the mechanisms for profit allocation. For effective power system management, fostering cooperation among EHs is essential, as such collaboration can provide mutual support during adverse conditions.

5.1.2. Cooperative management

Participants in competitive games prioritize maximizing their individual profits over achieving regional objectives. With advancements in energy conversion technologies such as combined heat and power units (CHPs), electric heat pumps (EHPs), absorption chillers (ACs), and power-to-gas units, the interdependency among different energy systems has significantly increased (Li et al., 2022). Therefore, it is essential to develop a coalitional framework for multi-energy systems within a networked topology so that different multi-vectored hubs can exchange energy or convert energy from one form to another according to demand. A cooperative energy management has been employed in Lo Prete and Hobbs (2016) and argued that collaboration of microgrids results in cost-effective energy dispatch.

Cooperative game theory involves forming coalitions where participants collaborate to optimize collective benefits, leveraging interdependencies for better outcomes than acting independently. These games often take a 'black box' approach, focusing less on the specifics of agreements, bidding strategies, or policies within the coalition, while the primary focus remains on achieving the maximum net profit or economic outcome (Lokeshgupta and Sivasubramani, 2019). Unlike non-cooperative games, where participants aim to maximize individual profits without regard for regional welfare, cooperative game theory-based optimization models prioritize achieving a globally optimal solution while respecting local objectives. A profit-sharing mechanism ensures equitable distribution of collective payoffs among players (Camarinha-Matos, 2016).

A cooperative strategy aligns regional goals with individual targets, enabling coalition members to minimize costs, enhance reliability, and reduce GHG emissions through collaboration and power exchange during adversities. Fair profit distribution, reflecting participant's contributions, ensures individual objectives are met (Long et al., 2019). The interdependence of heat, gas, and electricity systems underscores the suitability of cooperative game theory for managing MV-NEHs effectively.

Recent studies have explored cooperative microgrid management to harness the benefits of cluster-based operations. For instance, (Anvari-Moghaddam et al., 2017) introduces an energy management program integrating agents like a central controller and battery bank to enhance self-sufficiency and reliability. Cooperative strategies for multi-energy microgrids are proposed in Wouters et al. (2015), while (Fang and Yang.) focuses on single-carrier microgrid clusters for critical load distribution. In Bui et al. (2018), community energy management with demand response is examined, but excludes stochastic modelling of RESs. Similarly, (Zhao et al., 2020) uses stochastic optimization for multi-energy hubs but omits power transfer, fair cost allocation, EV roles, and demand response. A two-stage stochastic model in (Guo et al., 2021) addresses EV battery costs, RES uncertainties, and emissions impacts but lacks a multi-energy framework, power flow analysis, and cooperative fair payoff allocation.

The interdependence and interconnection of gas, electricity, heat, and ice energy systems significantly enhance system flexibility and reliability through joint operation (Salehi et al., 2022). In recent years, numerous studies have adopted cooperative approaches to harness the potential benefits of such integrated operations, highlighting their effectiveness in optimizing overall system performance.

Energy management is proposed in Karimi and Jadid (2021) for the multi-microgrid system. The paper uses the classic Shapley value for profit allocation among the MGs and considers stochastic analysis. A fair energy trading mechanism for the network of MGs based on cooperative game theory and classic Shapley value is discussed in Tan et al. (2021). The study in Amir Mansouri et al. (2021) investigates and analyzes both coordinated (cooperative) and uncoordinated operational schemes for multi-carrier energy systems, providing insights into their performance and efficiency.

Although flexible technologies, i.e., demand response and electric vehicles, are included in the study, the issues related to RES risks and uncertainties, networked topology, and impact on emissions are not addressed. The study in Alizadeh Bidgoli and Ahmadian (2022) proposes a deep learning-based stochastic energy management framework designed for systems with a multi-microgrid (MMG) structure. The study incorporates a flexible loading scheme. However, literature (Karimi and Jadid, 2021; Tan et al., 2021; Amir Mansouri et al., 2021; Alizadeh Bidgoli and Ahmadian, 2022) overlooked the multi-vectored energy system formulation, flexible loading (demand response) scheme, and PEVs. In (Ma et al., 2019), A cooperative framework is proposed for energy hub systems, incorporating the uncertain characteristics of photovoltaic (PV) prosumers and leveraging the conditional value at risk (CVaR) methodology. Additionally, (Tiwari and Singh, 2022) presents a cooperation-based optimal energy scheduling approach for networked multi-carrier energy hubs.

5.1.3. Fair cost allocation scheme

In cooperative game theory, participants will only play the game and collate if all the players receive gets profit. In Fan et al. (2018), a distributed optimization algorithm is proposed for a networked multi-vectored system. The system is managed by bargaining based on cooperative game theory among different participants. To incorporate the multi-vectored multi-microgrid system, the study (Zhong et al., 2022) proposes a stochastic and coordinated energy management strategy to analyze the day-ahead and intra-day scheduling for an integrated heat-electricity networked system. A deterministic cooperative energy management framework is proposed in Bahmani et al. (2021) for a heat-ice-electricity integrated networked system, incorporating a revenue allocation scheme based on the Shapley value. To address the collective interests of residential energy communities ECs), such as minimizing operating costs and reducing energy consumption, cooperative energy management is explored in Tostado-Véliz et al. (2022). A profit allocation mechanism for networked microgrid structures, based on the nucleus method, is discussed in Du et al. (2018). This study integrates ECs with plug-in electric vehicles PEVs) and flexible loads to lower net operating costs and reduce energy imports from the grid; however, it does not consider the multi-energy concept or the risks associated with renewable energy sources (RESs). In (Luo et al. (2019), cooperative energy management is developed to enhance the operational efficiency and reduce the costs of a multi-energy system (electricity and cooling). The Shapley value is employed to fairly distribute system costs among stakeholders.

While studies (Karimi and Jadid, 2021; Tan et al., 2021; Amir Mansouri et al., 2021; Alizadeh Bidgoli and Ahmadian, 2022; Ma et al., 2019; Tiwari and Singh, 2022; Fan et al., 2018; Zhong et al., 2022; Bahmani et al., 2021) emphasize cooperative approaches for the optimal scheduling of networked microgrids (MGs), a comprehensive investigation into networked systems integrating heat-electricity-ice-gas energy systems, along with the efficient incorporation of flexible technologies such as demand response (DR) and electric vehicles (EVs), remains lacking. The mentioned literature includes flexible demand side management, while cooling energy systems, advanced energy storage units, RES risk factors, and coalitional reliability aspects are not considered.

In addition, (Long et al., 2019; Karimi and Jadid, 2021; Tan et al., 2021; Tiwari and Singh, 2022), and (Bahmani et al., 2021; Tostado-Véliz et al., 2022; Du et al., 2018; Luo et al., 2019) employ the classic Shapley value method for profit allocation but overlook the impact of renewable energy sources (RESs) and electric vehicles (EVs) in the allocation process. Energy hubs (EHs) with high-RES penetration and other flexible technologies that contribute to reducing greenhouse gas (GHG) emissions should receive additional incentives to promote green energy adoption. Furthermore, references (Li et al., 2022; Lo Prete and Hobbs, 2016; Lokeshgupta and Sivasubramani, 2019; Camarinha-Matos, 2016; Long et al., 2019; Anvari-Moghaddam et al., 2017; Wouters et al., 2015; Fang and Yang.; Bui et al., 2018; Zhao et al., 2020; Guo et al., 2021; Salehi et al., 2022; Karimi and Jadid, 2021; Tan et al., 2021; Amir Mansouri et al., 2021; Alizadeh Bidgoli and Ahmadian, 2022; Ma et al., 2019; Tiwari and Singh, 2022; Fan et al., 2018; Zhong et al., 2022; Bahmani et al., 2021; Tostado-Véliz et al., 2022; Du et al., 2018; Luo et al., 2019) have not thoroughly investigated the benefits of advanced energy storage systems, such as pumped hydro storage and compressed air energy storage. Nonetheless, most existing cooperative-game formulations focus on static cost allocation; multi-timescale incentive schemes that link short-term operation with long-term investment signals remain limited. On the attributes side, such as green energy curtailment, financial risks associated with RES intermittency, and the reliability of coalitional frameworks, remain unaddressed. Additionally, critical carbon reduction strategies, such as power-to-gas technology and carbon capture and storage units, are not examined in the cited literature.

5.1.4. Transactive energy management

Although numerous studies (Bandeiras et al., 2020; An et al., 2018; Rezaei et al., 2022; Poursmaeil et al., 2021; Li et al., 2019; Saad et al., 2012; Hamidi et al., 2016; Chen and Zhu, 2017; Liu et al., 2018a; Xie et al., 2018; Jalali et al., 2017; Nasiri et al., 2020; Salehi et al., 2019; Zare Oskouei et al., 2021; Li et al., 2022; Lo Prete and Hobbs, 2016; Lokeshgupta and Sivasubramani, 2019; Camarinha-Matos, 2016; Long et al., 2019; Anvari-Moghaddam et al., 2017; Wouters et al., 2015; Fang and Yang.; Bui et al., 2018; Zhao et al., 2020; Guo et al., 2021; Salehi et al., 2022; Karimi and Jadid, 2021; Tan et al., 2021; Amir Mansouri et al., 2021; Alizadeh Bidgoli and Ahmadian, 2022; Ma et al., 2019; Tiwari and Singh, 2022; Fan et al., 2018; Zhong et al., 2022; Bahmani et al., 2021; Tostado-Véliz et al., 2022; Du et al., 2018; Luo et al., 2019) have focused on the interconnected framework and its control, many have overlooked a critical aspect of energy trading among energy hubs within networked systems. To address the complexities of networked energy systems, the Grid Wise Architecture Council (GWAC) introduced the concept of Transactive Energy (TE) (Martínez Ceseña et al., 2018). TE encompasses a set of economic and control mechanisms designed to enable microgrids (MGs) and EHs to maintain a balance between supply and demand within a networked structure (Zia et al., 2020). It operates using value as a fundamental operational parameter. TE is defined as "a set of economic and control mechanisms that enables the dynamic balance of supply and demand across the entire electrical infrastructure, utilizing value as a key operational parameter" (Ambrosio, 2016). The key attributes of Transactive Energy (TE) management are as follows:

- TE systems should offer coordinated self-optimization capabilities.
- Effective integration of multiple Distributed Energy Resources (DERs) should be ensured without compromising system reliability.
- Participants in the TE market are responsible for adhering to performance standards.
- TE systems should possess the properties of extensibility, adaptability, and scalability across various smart devices, participants, and geographic areas.
- Fair market opportunities within the TE system should be provided to all qualified participants.
- TE systems should enable auditability and observability at interfaces.

In addition, TE frameworks provide a basis for explicit demand-side flexibility, where flexible electrical and thermal loads, EVs, and storage are modelled as controllable resources within the multi-timescale coordination scheme.

5.2. Recent research developments

Recent studies have suggested the application of transactive energy TE) for managing energy exchange within networked systems. In Daneshvar et al. (2020)b, a stochastic model based on TE is proposed, where microgrids MGs) actively participate in local markets by buying and selling electricity. In (Daneshvar et al. (2022)a, a framework based on transactive energy management is developed for the multi-microgrid system. Although the free energy market mechanism is modelled for heat-electricity integrated energy hubs, the modelling of the cooling system, demand response, EVs, and fair and improved payoff allocation is not discussed. A chance-constrained-based TEM model to provide individual and collective interest for clustered MGs is presented in Daneshvar et al. (2020)c. The paper develops a framework which provides equal cost savings to all MGs while ensuring common interest. However, the modelling of the cooling system and flexible resources, along with the fairness and stability of the proposed payoff allocation, is not discussed. A dynamic pricing mechanism leveraging transactive energy (TE) for optimal coordination between microgrids (MGs) and distribution system operators (DSOs) is discussed in Liu et al. (2020). An intra-day peer-to-peer (P2P) market mechanism based on TE, enabling prosumers to trade with the grid or other prosumers, is proposed in (Khorasany et al., 2021a). In (Feng et al., 2020), a nucleolus-based payoff allocation ensures participants' individual interests but excludes renewable energy sources (RES) and electric vehicles (EVs) in the distribution model.

For multi-microgrid (MMG) electrical systems, power exchange between MGs enhances network reliability, allowing MGs to procure energy from the main grid or neighbouring MGs in local markets. A stochastic TE-based operational framework for MMGs with a double auction mechanism is introduced in (Khorasany et al., 2021b), though profit allocation, demand response, plug-in electric vehicles (PEVs), RES risks, and reliability metrics remain unaddressed. In (An et al., 2021), a business feasible mechanism is developed to calculate the optimal trading price for trading in the local community market. In (Jadidbonab et al., 2021), a self-scheduling virtual energy hub is modelled to interact in the electrical and thermal community market to increase its revenue. Literature (Daneshvar et al., 2020b, 2022a, 2020c; Liu et al., 2020; Khorasany et al., 2021a; Feng et al., 2020; Khorasany et al., 2021b; An et al., 2021; Jadidbonab et al., 2021) investigates the energy trading mechanisms in the MMG electrical system; however, the multi-energy concept is not explored in detail.

A detailed multi-objective analysis of MV-NMG systems (heat-electricity-ice) from economic, environmental, and reliability perspectives, integrating electric vehicles (EVs), demand response, and advanced energy storage systems such as compressed air and pumped hydro storage, remains underexplored. While existing studies on multi-microgrid (MMG) systems address uncertainty and cluster management, gaps persist in EV modelling, demand response and equitable profit allocation. A joint chance-constrained framework for power exchange between MMGs and the central grid is proposed in (Bazmohammadi et al., 2019). Cooperative energy management among energy hubs, incorporating power exchange, wind curtailment, and thermal/electrical storage with power-to-gas integration, is also explored in (Gholizadeh et al., 2019). A transactive energy-based framework for MGs with 100 % renewable energy (RES) is proposed in (Daneshvar et al., 2021a), featuring a local energy market to minimize energy costs. However, flexible resources' roles in economic and environmental outcomes are not thoroughly examined. The advancement of energy conversion technologies, including combined heat and power (CHP) units, electric heat pumps (EHPs), absorption chillers (ACs), and power-to-gas systems, has increased the interdependence of diverse energy systems.

Further, to realize the optimal and reliable solution for the region, the network or coalitional formation of energy hubs needs to be implemented. This allows energy hubs to support nearby energy hubs during the critical conditions and thus ensures high reliability and independence from the main grid. Therefore, a coalitional framework for multi-energy systems within a networked topology should be established so that different multi-vectored hubs can exchange energy or convert energy from one form to another according to demand. In network formation, the most important task is to maintain time-to-time load-generation balance and energy balance among energy hubs. This can be ensured by implementing transactive energy management. Therefore, with cooperation-based transactive energy management, a network of multi-vectored energy hubs framework can be modelled such that it ensures the global objectives, such as minimizing energy cost and emissions, while improving the self-reliability of the network. Moreover, the framework should be able to fulfil the individual objectives or goals that include achieving the profit based on the energy hub's special attributes, such as their ability to reduce carbon emissions and reliability factors. To showcase the key attributes and recent trends of integrated multi-energy systems, Table 1 summarises key integrated multi-energy studies, classifying them by energy vectors, decision time scales (day-ahead, intraday, real-time, planning), and coordination/optimization mechanisms, including uncertain variables and ways of addressing flexibility.

6. Low emission energy system models

In recent decades, the rising population has significantly increased the consumption of natural resources, with fossil fuels being the primary source of energy worldwide. However, their use is associated with major drawbacks, including high pollution and greenhouse gas (GHG) emissions. To mitigate these challenges, there is an urgent need for sustainable solutions. As a result, the modelling of low-emission energy systems and strategic energy planning has garnered considerable attention to meet global energy demands while reducing GHG emissions (Esapour et al., 2023).

The incorporation of low-emission energy models, which include technologies such as Power-to-Gas (P2G), Carbon Capture and Storage (CCS), and carbon markets, has emerged as a critical approach in combating climate change and transitioning to a sustainable energy future. As the globe grapples with the issues of rising greenhouse gas emissions, global warming, and the depletion of fossil fuel resources, there is an urgent need to transition to cleaner, more sustainable energy sources. By merging different technologies, this integrated energy model provides a realistic solution to the pressing demand for reducing greenhouse gas emissions and minimizing the environmental impact of traditional energy sources (Alsanousie et al., 2023).

The Power-to-Gas (P2G) concept, which involves transforming excess renewable energy into storable gases such as hydrogen or synthetic natural gas (SNG), is at the core of this energy strategy. This approach enables the efficient use of renewable energy by storing excess energy produced during periods of high generation and using it during periods of low renewable energy production. P2G technology, which converts renewable energy into storable gases, enables the integration of intermittent renewable energy sources into existing energy infrastructure, resulting in a dependable and flexible energy supply (Chen et al., 2023). For instance, surplus electricity from renewable sources can be utilized for hydrogen production via electrolysis and stored in dedicated hydrogen storage tanks.

Additionally, the implementation of Carbon Capture, Storage, and Utilization (CCS-U) systems presents an effective approach to reducing emissions. Carbon Capture and Storage (CCS) is a promising technology designed to minimize emissions from fossil fuel-based power plants and industrial processes (Zhang et al., 2023). Carbon emissions are captured at the source by CCS technology, preventing them from being discharged into the atmosphere. The captured CO_2 is then transported and stored in underground geological formations that ensure the containment of emissions for the long term. Thus, with the implementation of CCS-U units, significant volumes of CO_2 emissions can be avoided. Thus, ensuring low emissions results in mitigating the impact of greenhouse gases on climate change.

However, the independent deployment of CCS-U technology is economically challenging and poses a potential risk of carbon leakage (Limb et al., 2022). The incorporation of carbon markets boosts the low-emission energy paradigm even further. By putting a price on carbon, carbon markets create economic incentives to reduce emissions. This market-based method allows energy and power systems to trade carbon credits, giving emissions reductions a monetary value. Carbon markets encourage the adoption of cleaner and greener technologies through imposing a price on carbon emissions (Moradi et al., 2022).

Table 1
Comparative overview of system attributes and multi-timescale, flexibility-integrated coordination frameworks in multi-energy hub systems.

Ref.	System context and flow of energy vectors	Timescale structure	Management Approaches	P2X pathway(s) and Demand-side flexibility	Uncertain variables
(Cai et al., 2020)	Resilient microgrid with DERs; Power, heat	Short-term MPC horizon with repeated optimization	Central robust MPC	No P2X; Flexibility mainly via storage & re-dispatch	RES output, load
(Daneshvar et al., 2020a)	Transactive renewable microgrid; Power, heat	Two-stage (DA scheduling + RT adjustment)	Robust–stochastic TE framework; distributed coordination	No P2X; Price-based DR within TE framework	RES, load, market prices
(Najafi et al., 2021)	Smart energy hub in DA & regulation markets; Power, heat, gas	DA + balancing/ regulation market	Risk-based self-scheduling	No P2X; Flexible loads providing ancillary services	RES, load, DA & prices
(Hou et al., 2020)	Urban energy hub; Power, heat, cooling	Real-time rolling horizon within a day	Rolling chance-constrained control	–	RES, load forecast errors; operational
(Xu et al., 2022)	Future integrated energy system with large-scale hydrogen; Power, gas, and hydrogen	Multi-period day-ahead / operational	Centralized coordinated optimization	P2H, Flexible electrical and hydrogen loads	RES, load, electricity & gas prices
(Zheng et al., 2023)	Integrated system with chemical-looping methane reactor and CCUS; Power, gas, CO_2	Multi-period operation	Centralized low-carbon EMS	P2synthetic methane + CCS-U; flexible energy conversion & storage	Fuel, carbon prices
(Qian et al., 2020)	Integrated energy system with carbon trading; Power, heat, gas	Multi-interval operation	Fully decentralized bi-level management; distributed ADMM-type coordination with carbon-trading incentives	P2G / sector coupling; DR of flexible load participation in carbon-aware dispatch	RES, load, carbon prices
(Ju et al., 2022)	Nearly-zero-carbon integrated energy system in rural area; Power, heat, gas, CO_2	Multi-period DA/ operation	Coordinated low-carbon optimization with CCS and P2G	P2G + CCS-U; DR of flexible loads and storage	RES, load, carbon prices
(Xu et al., 2024)	Electric–hydrogen multi-energy system with hybrid storage; Power, hydrogen, gas	DA–intraday–RT mixed scheduling	Centralized multi-timescale coordinated EMS	P2H with electrolysis & storage; DR and hydrogen flexibility supporting the power grid	RES, load, prices
(Bornemann et al., 2025)	Decentralized multi-energy system with hydrogen integration; Power, heat, hydrogen	Long-term multi-stage expansion planning	Multi-stage planning, some decentralization of agents	P2H with electrolysis & storage; no DR	Fuel prices, demand growth, and RES scenarios
(Li and Li, 2025)	Multi-energy production units in real-time market; Power, heat, gas	Distributionally robust RT	Risk-averse EMS with coordinated offering and RT dispatch	No P2X; DR of flexible industrial and heating loads	Market prices, RES, load, fuel & carbon prices
(Alizadeh Aliabadi et al., 2025)	Multi-microgrid planning with RT market; Power, heat	Long-term planning + RT market	Stochastic planning: RT outcomes propagated into design	No P2X; DR and flexible loads in MGs	RES, RT prices, load;
(Cao et al., 2022)	Energy hub in hybrid power–gas–carbon markets; Power, gas, heat, CO_2	DA & RT power; DA gas & carbon	Multi-level DRO-based coordinated management in coupled markets	P2G / CO_2-to-fuel implicit via carbon market; Price-based DR in hybrid market participation	RES, load, electricity, gas & carbon prices
(Wang et al., 2024)	Integrated energy system with a dynamic energy hub; Power, heat, cooling, gas	DA, intraday, near-RT	Hierarchical multi-time-scale EMS; coordinated dual DR	P2G; electric & thermal DR	RES, demand, prices in different time scales

Thus, ensures to model a low-emission and low-cost energy system framework. The typical integration of Power-to-X and CCS-U technologies in the updated energy hub, including their detailed integration, is shown in Fig. 10.

6.1. Recent research developments

Renewable energy curtailment has emerged as a significant challenge in integrated energy systems due to mismatched generation and consumption patterns (Ma et al., 2021). To address this, storage technologies like power-to-gas (P2G) and hydrogen storage have gained prominence. Studies such as (Yuan et al., 2020; Xu et al., 2022) have explored P2G's impact on multi-vector energy hubs, electricity systems, and strategies for integrating P2G with natural gas markets. Optimization models combining P2G with CCHP systems (Yang et al., 2020), electric vehicles (Chen et al., 2021) and fuel cells (Fragiacomo and Genovese, 2020) have also been proposed. Additionally, scenario-based models incorporating demand response (Alizad et al., 2022) and frameworks addressing renewable energy curtailment and environmental impacts (Zheng et al., 2023) have been presented. Further, references (Huang et al., 2022; Qian et al., 2020; Zhang et al., 2022b; Xu et al., 2023) propose integrated models of carbon capture, P2G, introducing modern robust optimization algorithms such as alternating direction method of multipliers (ADMM) (Qian et al., 2020) and emissions trading to achieve low-carbon energy systems. These include life cycle assessments (Cheng et al., 2020), ladder-type carbon emission approaches (Wang et al., 2022; Yang et al., 2023) and analyses of wind power uncertainties (Yang et al., 2023) and (Wu and Li, 2023). Advanced optimization techniques, such as information gap theory (Ju et al., 2022), stochastic programming (Honarmand et al., 2021) and robust frameworks (Dolatabadi et al., 2017a), enhance system flexibility (Dolatabadi et al., 2017b) and minimize dispatch costs are implemented in these research studies.

Even though (Esapour et al., 2023; Alsanousie et al., 2023; Chen et al., 2023, 2021; Zhang et al., 2023, 2022b; Limb et al., 2022; Moradi et al., 2022; Ma et al., 2021; Yuan et al., 2020; Xu et al., 2022, 2023; Yang et al., 2020, 2023; Fragiacomo and Genovese, 2020; Alizad et al., 2022; Zheng et al., 2023; Huang et al., 2022; Qian et al., 2020; Cheng et al., 2020; Wang et al., 2022; Wu and Li, 2023; Ju et al., 2022; Honarmand et al., 2021; Dolatabadi et al., 2017a) discuss the role of battery electric vehicles, advanced storage systems, such as pumped hydro storage, adiabatic and compressed air storage, remain underexplored. Similarly, hybrid power-to-X systems and self-independence factors (SIF) in energy hubs, which enhance efficiency and reduce network losses, are seldom addressed. Further, advanced storage technologies such as pumped hydro, adiabatic CAES, or hybrid P2X pathways appear

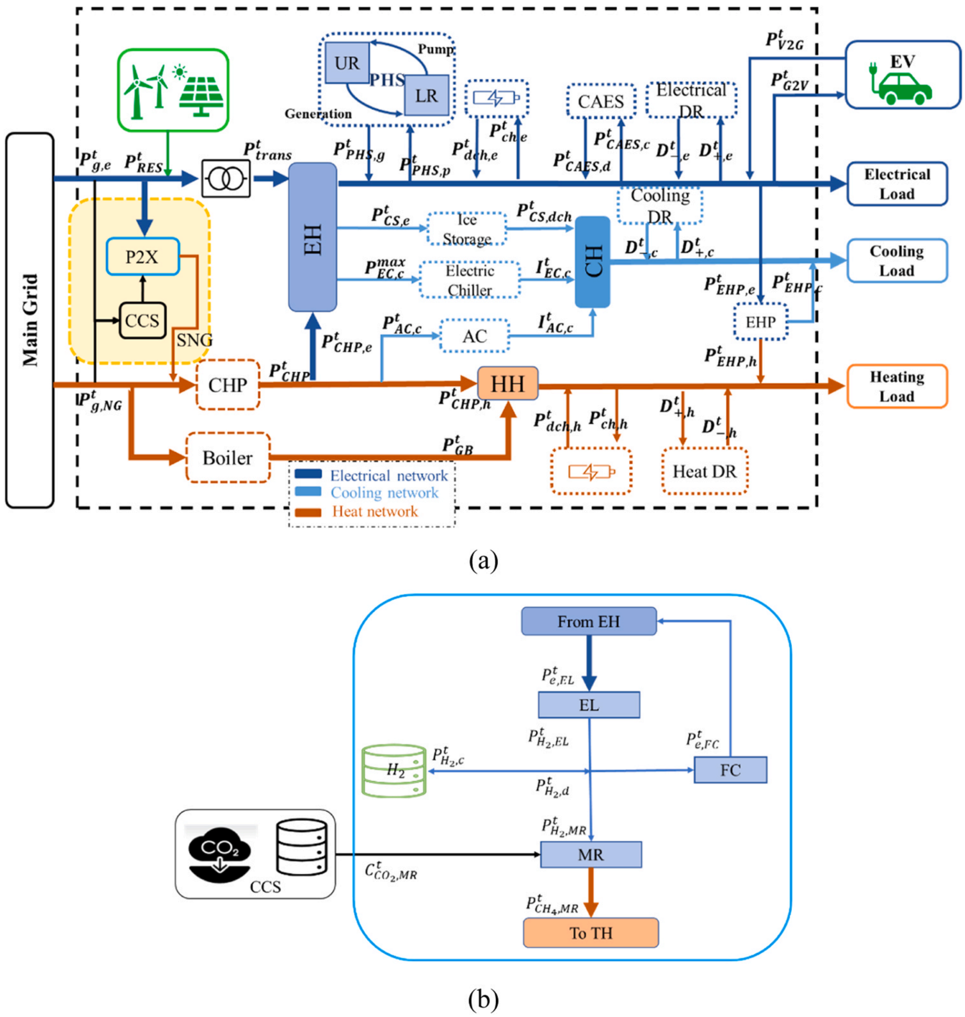

Fig. 10. Low-emission multi-vectored energy hubs integrating Power-to-X and CCS-U technologies.

less frequently in the current literature, indicating opportunities for further work. Similarly, while CCS integration is well recognized for its environmental benefits, more detailed techno-economic assessments linking CCS with utilization (CCS-U) operation with emission trading mechanisms would enhance the current body of research. Thus, developing an emission market mechanism to transform integrated low-emission multi-vector energy hubs into both economically and environmentally viable systems is imperative.

7. Power system integration with energy hubs

The development of optimization models for multi-energy distribution systems has relied heavily on benchmark test networks, each chosen to highlight specific operational challenges. The 5-bus IEEE system (Monemi Bidgoli et al., 2021; Barati et al., 2024) integrates electricity, heating, and cooling to address RES stochasticity, with applications in desalination. The 6-bus IEEE system (Mirzaei et al., 2020; Alabdulwahab et al., 2015; Wu et al., 2018; Nasiri et al., 2020; Karimi and Jadid, 2021; Zhu et al., 2024) explores DR programs, controllable resources, and battery storage, with a bi-level framework developed in (Nasiri et al., 2020) to study battery efficiency. An 8-bus system is designed and discussed, considering the thermal systems in (Ding et al., 2024).

The 14-bus IEEE system (Chen and Zhu, 2017; Aeggegn et al., 2025) models non-cooperative multi-microgrid systems and hydrogen integration, while the 13-bus IEEE system (Saleh et al., 2016) examines microgrid clustering during blackouts for improved resiliency while 24-bus system is described in (Ahmad et al., 2024). Smaller networks, such as the modified IEEE 18-bus system (Bandeiras et al., 2020), have been applied in day-ahead scheduling problems, with emphasis on factory-based supply of electricity and thermal loads.

Moderate IEEE networks, such as the 30-bus (Luo et al., 2024), and 33-bus (Mirzapour-Kamanaj et al., 2020; Dabbaghjamanesh et al., 2021; Hemmati et al., 2020; Amir Mansouri et al., 2021; Xu et al., 2024; Lyu and Cheng, 2023; Carpinelli et al., 2024; Hu et al., 2024) support RES uncertainty modelling, integrating hydrogen and thermal storage. Among these, the IEEE 33-bus system has become the most widely adopted framework, appearing in numerous studies. Its moderate size makes it suitable for detailed modelling of distributed energy resources (DERs), storage units, and demand response programs, while still being computationally tractable. For instance, (Amir Mansouri et al., 2021) developed an integrated structure combining electricity, heating, and cooling with advanced storage units to enhance system flexibility. Researchers have used this system to explore objectives ranging from cost minimization and voltage regulation to profit maximization and emission reduction, often extending the model to include thermal, cooling, or hydrogen subsystems.

At the other end of the spectrum, larger systems like the modified IEEE 123-bus (Zhang et al., 2014) and the IEEE 118-bus (Li et al., 2024; Ma et al., 2024) provide a richer environment for testing scalability. The 123-bus case allows for detailed placement of combined heat and power (CHP) units under varying ambient conditions, while the 118-bus system has been used to integrate electricity, natural gas, and thermal networks, or to examine hydrogen trading mechanisms. These larger testbeds highlight the complexity of multi-vector energy flows and the need for advanced solvers such as CPLEX, GUROBI, or ADMM.

Beyond IEEE standards, alternative benchmarks have also been introduced. The hybrid distribution system of Alexandria, Egypt (El-Zonkoly, 2017) incorporates residential, commercial, and industrial loads in a DC microgrid setting, solved with metaheuristic algorithms such as GA, PSO, ABC, and FA. The modified CIGRE benchmark (Bazmohammadi et al., 2019) has been used for simplified scheduling studies, focusing solely on electricity and neglecting heating and cooling networks. These non-IEEE systems provide context-specific insights, demonstrating how optimization strategies perform under different load compositions and network structures.

Taken together, the choice of test network strongly shapes the scope of each study. Smaller systems allow for detailed exploration of DER constraints and operational strategies, while larger networks enable investigation of multi-energy interactions and scalability. Non-IEEE benchmarks add diversity by reflecting real-world hybrid microgrids. This progression from compact IEEE test cases to complex, multi-vector networks illustrates the broader trajectory of research: moving steadily toward integrated, large-scale models that capture both technical and economic dimensions of modern energy systems.

Advanced technologies, such as grey wolf optimization (Aeggegn et al., 2025), electrolyzers (Bornemann et al., 2025), and pumped storage hydropower (Zhu et al., 2024), enhance flexibility (Ma et al., 2024) and are discussed and implemented in power systems, yet most IEEE-based test implementations treat the energy hub as a quasi-static equivalent and rarely integrate multi-timescale coordinated control with demand-side flexibility, or game-theoretic incentive mechanisms within the power-system benchmark. Table 2 articulates the integration of electricity networks and the MVEH concept in different studies.

8. Uncertainty and risk in multi-energy systems

Understanding and managing uncertainty and risk is critical for ensuring the reliability, efficiency, and resilience of multi-energy systems. As these systems become increasingly integrated and dependent on variable renewable sources, addressing both epistemic and aleatory uncertainties becomes essential. This section explores the key sources of uncertainty and risk, as well as the advanced methodologies developed for their effective management.

8.1. Uncertainty management in energy systems

Uncertainty is typically the absence of certainty, a polysemic term (with "poly" meaning "many" and "sema" meaning "sign"), defined as "*a continuous evaluation of the truth value of a proposition, such as in relation to the occurrence of an event*" (Joshi and Luong, 2022). Uncertainties can be broadly classified into two categories, the first source, uncertainty due to limited knowledge (Epistemic) illustrated in Fig. 11, arises from data limitations and incomplete information but can be reduced through better observations and modelling techniques (e.g., lack of precise data on future energy prices affecting investment decisions, or uncertainty in the performance of emerging energy storage technologies). These uncertainties can be mitigated with improved data, research, and expert input (Rodriguez-Matas et al., 2025).

The second source, uncertainty due to variability shown in Fig. 12, is inherent randomness and cannot be fully eliminated, even with increased knowledge (e.g., solar irradiance, wind speed, demand fluctuations due to seasonal changes). These uncertainties arise from the natural variability of energy systems, and no amount of data can fully predict or control them (Alizadeh et al., 2024).

Uncertainties can be managed through various approaches, as illustrated in Fig. 13, with scenario-based techniques being the most prominent (Shi et al., 2024). These techniques address uncertainties where assigning precise probability measures is difficult or impossible. Specifically, this method applies to situations that may result in multiple potential outcomes, making it challenging or even infeasible to determine the probability of a specific result. Another approach involves probabilistic techniques, which apply to situations where uncertainty can be clearly defined and quantified statistically, or where uncertainties can be expressed and captured using statistical methods (Sun et al., 2024). These techniques handle uncertainties for which ample historical or experimental data allow the derivation of probability distributions. However, certain uncertainties do not fit neatly within purely probabilistic or scenario-based frameworks, prompting the introduction of hybrid techniques by practitioners to deal with cases where both quantitative (probabilistic) and qualitative (possibilistic or fuzzy) information or interval bounds (lower and upper limits) are available (Azimi et al., 2024).

Traditional energy system models often assume worst-case scenarios for key parameters like energy prices and demand, simplifying computations but leading to unrealistic results. In (Shahryari et al., 2019) emphasized that focusing only on the building level ignores broader urban energy dynamics, while in (Sharma et al., 2024), the need for diverse energy scenarios to better capture uncertainties is highlighted. Addressing these uncertainties requires considering multiple possible scenarios and their probabilities, enabling a more flexible decision-making framework. Techniques like scenario analysis and probabilistic modelling help planners assess future possibilities (Li and Li, 2025) demonstrate how integrating demand response in microgrids enhances adaptability, while (Liu et al., 2024a) show that fuzzy logic improves energy system regulation under fluctuating renewables. Advancements in computational methods and multi-criteria decision-making frameworks are essential to improving model reliability and adapting to emerging uncertainties in integrated energy systems.

New sources of uncertainty have recently emerged in the dynamics of multi-carrier energy systems due to the increasing integration of different energy carriers, coupled with renewable energy resources (RERs) and the growing network of electric vehicles (EVs). Moreover, shifts in local regulations and market behaviour accentuate the challenges faced by researchers analyzing these systems. In the real world, factors such as load demand, energy prices, solar radiation, and wind speed exhibit erratic and unpredictable behaviour, posing challenges for achieving optimal performance in operations related to these energy hubs. The uncertainty in these hubs, i.e., Integrated Energy Systems (IESs), arises from multiple sources such as intermittent renewable generation, fluctuating multi-vector demand, and volatile market prices (Kiani-Moghaddam et al., 2023). These factors jointly impact operational efficiency and investment decisions, necessitating robust energy management strategies. Optimization techniques, particularly for Smart Energy Hubs, have been developed to address these challenges. For example, the Mixed-Integer Linear Programming (MILP) technique supports operational planning in gas-integrated MVEHs, while scenario-based stochastic optimization facilitates coordinated scheduling across electricity, gas, hydrogen, and thermal sectors, aided by power-to-gas (P2G) systems (Prina et al., 2020). Hybrid solar-wind models account for generation variability, though some neglect market price uncertainty. Stochastic frameworks incorporating Monte Carlo simulations and k-means clustering have emerged to handle both types of uncertainty (Ahmed et al., 2024). Additionally, two-stage stochastic models assist in sizing Distributed Energy Resources (DERs) under demand and environmental variability (Ji et al., 2025), while decomposition and heuristic methods, such as deep repulsion optimization, improve scalability and multi-domain energy coordination (Gharibi et al., 2025). The integration of real-time market signals into these frameworks enhances their responsiveness, enabling better handling of day-ahead (DA) price and renewable generation uncertainties. In residential smart energy hubs, these models improve photovoltaic (PV) forecasting and planning. Techniques like Information Gap Decision Theory (IGDT) support risk-averse planning by enhancing resilience, reducing emissions, and controlling costs (Alizadeh Aliabadi et al.,

Table 2
Review of energy vectored coupled power system configurations.

Ref.	Test system	Objectives	Solvers	Coupling energy vector	Assumption	Main constraints
(Zhang et al., 2014)	Modified IEEE 123 bus	Maximize DER generation and the recovered thermal output	• Advanced Interactive Multidimensional Modelling System • CONOPT	Electricity, water, thermal, and natural gas	• The CHP units are located at each bus • Ambient temperature has a significant impact on the DG generation, • The local optimum is acceptable • Losses, pressure limits, head loss, and the capacity of pipelines are built as a nonlinear model.	• Bus voltage limit • Capacity of shunt capacitors • Thermal constraints of lines • Power balance • Nodal water head • Ambient temperature bound
(El-Zonkoly, 2017)	Hybrid distribution system of Alexandria, Egypt	Minimize operation cost	• Genetic Algorithm • Particle Swarm Optimization • Artificial Bee Colony • Firefly Algorithm	Electricity, cooling, thermal	• A hybrid DC microgrid is considered, • The DER is formulated as a non-linear model, • The expansion planning is not the focus of this work, • Different residential, commercial, and industrial loads are considered.	• Bus voltage limit • Energy balance • Battery charging and discharging constraints • Diesel generator limits • Reactive power balance • Load shedding constraints • Network gas supply limit • DER capacity limit
(Mirzapour-Kamanaj et al., 2020)	IEEE 33 bus	Minimize operation cost	• General algebraic modelling system (GAMS) • Mixed-integer linear programming (MILP)	Electricity, thermal, natural gas	• The wake effect is neglected. • The self-discharging rate of energy storage systems is zero • The electricity prices follow the real-time tariffs.	• Active and reactive power balance • Heat balance • DER capacity limit • Voltage limit • Maximum input gas to CHP and boiler • Maximum trading with the electricity grid
(Wang et al., 2016)	IEEE 33 bus	Minimize voltage deviations and operation cost	• Monte Carlo simulation	Electricity	• The distribution system consists of three MGs, • The electrical loads consist of critical and interruptible loads, • The scenario reduction is used to reduce the complexity	• Active and reactive power balance • Electric power flow • Voltage limit • DER capacity limit
(Bandeiras et al., 2020)	Modified IEEE 18 bus	Minimize operation cost	• General algebraic modelling system (GAMS) • MATLAB software	Electricity, thermal	• The proposed model only considers the day-ahead scheduling, • All factories can supply the electrical demand, • Thermal load can be supplied by the factories located within the same thermal group, • The scheduling is performed for 24 h, • The maintenance cost of RES is considered zero, • The mechanical details of turbines and generators are ignored.	• DER capacity limit • Ramp-up and ramp-down limit of DER • Storage constraints • Minimum on/off time of DER • Electric power flow • Maximum energy trading • Energy balance
(Hemmati et al., 2020)	IEEE 33 bus	Minimize operation cost	• General algebraic modelling system (GAMS) • SCENRED	Electricity, thermal	• Only electricity and thermal loads are considered, • The wake effect is neglected. • The self-discharging rate of energy storage systems is zero, • The scheduling is performed for 24 h,	• Transformer active and reactive power limits • Heat pump constraints • Energy storage constraints • Boiler constraints • CHP constraints • Minimum on/off time of DER

(continued on next page)

Table 2 (*continued*)

Ref.	Test system	Objectives	Solvers	Coupling energy vector	Assumption	Main constraints
						• Ramp-up and ramp-down limit of DER • Electricity and heat balances • Power flow constraints • Natural gas network constraints
(Nikzad and Samimi, 2021)	IEEE 33 bus	Maximize net profit	• MATLAB software • Probability metric-based approximation	Electricity	• Generation capacity in each period may vary, • The sensitivities of customers to price are different, • The generation cost is constant in all periods, • The self-discharging rate of energy storage systems is zero, • Heat and natural gas networks are not considered.	• Demand response constraints • Uncertainty modelling
(Xie et al., 2018)	IEEE 33 bus	Minimize operation cost	• Analytical target cascading (ATC) • General algebraic modelling system (GAMS) BARON solver	Electricity	• The wake effect is neglected, • The self-discharging rate of energy storage systems is zero, • The electricity prices follow the real-time tariffs.	• Generation limits of conventional sources • Ramp-up and ram-down limits • Power flow constraints • Spinning reserve constraints • Energy storage constraints • Power balance equation
(Guo et al., 2021)	IEEE 33 bus	Minimize operation cost and emissions	• General Algebra Modelling System (GAMS) • CPLEX solver	Electricity	• The DER is distributed in different nodes, • The electricity prices follow the real-time tariffs, • Heat and natural gas networks are not considered.	• Active and reactive power balance equations • Thermal unit constraints • Voltage limits • Electric vehicle constraints • RES constraints • Demand response formulation
(Amir Mansouri et al., 2021)	IEEE 33 bus	Minimize operation cost	• General Algebra Modelling System (GAMS) • CPLEX solver	Electricity, cooling, thermal	• Three residential, commercial, and industrial energy hubs are considered, • The peer-to-peer trading among energy hubs is not possible in the uncoordinated mode, • The loads are considered for four seasons, • The same component is considered in all of the energy hubs, • The hydrogen section is ignored.	• CHP constraints • Boiler constraints • Electrical heat pump constraints • Energy storage constraints • Chiller constraints • Electrical, thermal, and cooling balances • Coordinated power transaction constraints
(Alizadeh Bidgoli and Ahmadian, 2022)	IEEE 33 bus	Minimize operation cost	• ANN technique • General Algebra Modelling System (GAMS) • DICOPT solver	Electricity	• The electricity prices follow the real-time tariffs, • Heat and natural gas networks are not considered, • The energy storage system is installed alongside each RES, • Four MGs are considered, • The wake effect is neglected, • The self-discharging rate of energy storage systems is zero,	• RES constraints • Gas turbine constraints • Active and reactive power balances • Capacity of DER • Energy storage constraints • Voltage limits

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Table 2 (*continued*)

Ref.	Test system	Objectives	Solvers	Coupling energy vector	Assumption	Main constraints
(Du et al., 2018)	IEEE 33 bus	Minimize operation cost	• Nucleolus-based fair cost allocation method • General Algebra Modelling System (GAMS) • CPLEX solver	Electricity, thermal	• The charging and discharging efficiencies are the same, • The self-discharging rate of BES is zero, • The maintenance cost of RES is zero, • The electrical and thermal trading among energy hubs is provided, • The scheduling duration is 168 h.	• Charge/discharge constraints of energy storage • Energy balances • Capacity of DER • Voltage limits • Reactive balance
(Bazmohammadi et al., 2019)	Modified CIGRE benchmarks	Minimize operation cost	• Monte-Carlo algorithm	Electricity	• The scheduling duration is 24 h, • The wake effect is neglected, • Heat and natural gas networks are not considered, • The network constraints are neglected, • Heating and cooling sections are neglected.	• Power balance • Upper-bound of energy trading balance • Energy storage constraints
(Li et al., 2024)	IEEE 118 bus	Minimize operation cost	• Yalmip platform in MATLAB • CPLEX solver	Electricity, thermal, natural gas	• The wake effect is neglected, • Heat network constraints are considered, • The electricity prices follow the real-time tariffs, • The expansion planning is not the focus of this work, • The self-discharging rate of energy storage systems is zero	• Energy storage constraints • Voltage and current constraints • AC power flow • Heating network constraints • RES generation capacity • Maximum trading with the upstream network • Electrical and thermal balances • CHP constraints • Natural gas usage by CHP
(Ma et al., 2024)	IEEE 118 bus	Maximize operational revenue	• Alternating direction method of multipliers	Electricity, hydrogen	• The electricity prices follow the time-of-use tariffs, • The heating and cooling demand is neglected, • Water-energy nexus is out of the scope of this work.	• Hydrogen agent constraints • RES agent constraints • Hydrogen storage tank • Hydrogen compressor • Power balance • Energy storage constraints

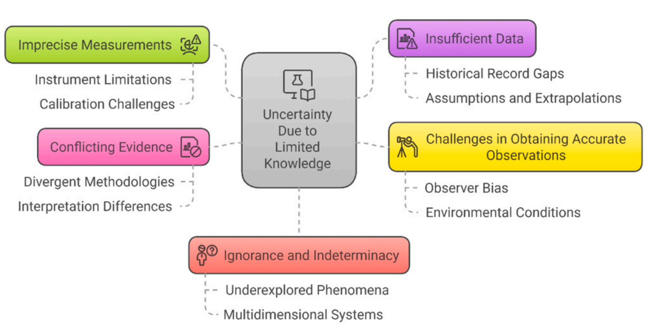

Fig. 11. Uncertainty due to limited knowledge.

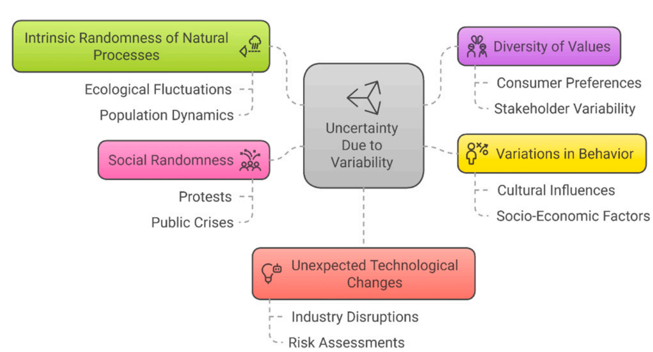

Fig. 12. Uncertainty due to variability.

2025).

Despite advancements in uncertainty modelling, there remains a gap in stochastic optimization frameworks that comprehensively integrate subsystem interactions within different MVEH configurations (Dolatnia et al., 2025; Nojavan and Khoudeh, 2025). Addressing these interdependencies is essential for developing resilient energy management strategies that ensure sustainable and cost-effective energy hub

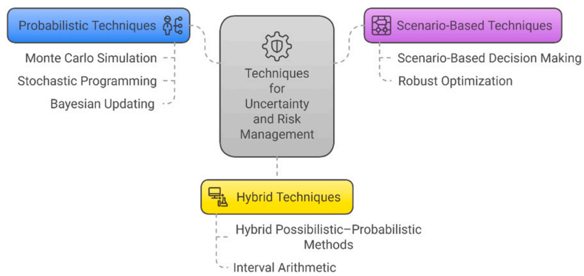

Fig. 13. Techniques used in handling uncertainties.

operations.

8.2. *Risk management in energy systems*

This section focuses on enhancing the operation of MVEHs under uncertain conditions using risk-averse optimization methods. It highlights the growing complexity of managing multiple interconnected energy carriers, including electricity, gas, water and thermal systems (Liu et al., 2024b). To tackle these challenges, a range of stochastic modelling approaches, such as Conditional Value-at-Risk (CVaR), Second-order Stochastic Dominance (SSD), and MILP-based technical constraints, are employed to improve forecasting accuracy and system reliability (Daneshvar et al., 2022b; Salyani et al., 2025). Risk-aware planning strategies are explored through hybrid energy configurations that incorporate wind turbines, energy storage systems (ESS), compressed air storage, and cooling demands. A modified Grasshopper Optimization Algorithm (MGOA) is utilized to strike a balance between

Table 3
Uncertainties and risk management techniques in energy systems.

Method	Description	Strengths	Limitations	Applications, main parameters
Conditional Value-at-Risk (CVaR) (Ma et al., 2019; Moradi et al., 2022; Alizadeh et al., 2024; Liu et al., 2024b; Salyani et al., 2025),	Measures expected losses beyond a given confidence level	Captures extreme outcomes, improves robustness of decision-making	Requires accurate probability distributions, computationally intensive	Energy hub scheduling, renewable integration, storage planning, solar, electricity price, natural gas price
Value-at-Risk (VaR) (Daneshvar et al., 2022b; Liu et al., 2024a; Li and Li, 2025; Dong et al., 2024)	Estimates the maximum loss over a time period at a certain confidence level.	Simple to compute, widely used in financial modelling.	Does not provide insights beyond the threshold, limited for nonlinear systems	Short-term operation planning, budget risk estimation
Stochastic Programming (Lokeshgupta and Sivasubramani, 2019; Guo et al., 2021; Karimi and Jadid, 2021, 2019; Tan et al., 2021; Amir Mansouri et al., 2021; Tiwari and Singh, 2022; Khorasany et al., 2021a; Xu et al., 2022; Chen et al., 2021; Alizad et al., 2022; Dolatabadi et al., 2017a; Aeggegn et al., 2025; Ma et al., 2024; Shahryari et al., 2019; Dong et al., 2024; Hakimi et al., 2021; Karimi et al., 2021)	Optimizes decisions by considering multiple scenarios based on probability.	Handles uncertainty explicitly, provides flexible decision pathways.	High computational demand, scenario generation can be complex.	Generation dispatch, long-term planning, multi-energy systems, Electrical, cooling and heating loads, the output power of RESs and EV drivers' behavior, electricity price
Robust Optimization (Wu and Li, 2023; Honarmand et al., 2021; Najafi et al., 2022; Zhou et al., 2018; Gupta and Gupta, 2015; Shams et al.)	Plans for the worst-case outcomes within a defined uncertainty range	Ensures reliable operation under all possible cases, no need for probabilities	Often conservative, may lead to over-engineered solutions	Critical infrastructure operation, microgrid design, Wind, solar, electric load, thermal load variabilities
Probabilistic Scenario-Based Analysis (Sharma et al., 2021; Sun et al., 2024; Ma et al., 2024)	Evaluates system performance under different pre-defined future conditions	Intuitive and easy to implement, useful in planning stages	Subjective scenario selection, may miss rare or extreme events	Energy policy modelling, infrastructure investment, solar, Wind, Load uncertainties
Monte Carlo Simulation (Daneshvar et al., 2020b; Khorasany et al., 2021b; Ahmed et al., 2024; Nojavan and Khoudeh, 2025; Sharma et al., 2021)	Uses random sampling to estimate system behavior under uncertainty	Provides probabilistic insights, supports sensitivity analysis	Time-consuming, depends heavily on number of simulations and input quality	Renewable forecasting, reliability analysis
Chance-Constrained Programming (Zhao et al., 2020; Daneshvar et al., 2020c)	Allows constraints to be violated within an acceptable probability range	Balances flexibility and reliability, suitable for probabilistic constraints	Needs good statistical estimates, may not ensure performance in all cases	Reserve allocation, network design under uncertainty, Electricity prices, loads, solar and ambient temperatures
Information Gap Decision Theory IGDT (Daneshvar et al., 2021a; Ji et al., 2025; Shi et al., 2024; Azimi et al., 2024)	Optimizing a multi-energy system, considering different risk attitudes under demand uncertainty, multi-objective framework for an integrated energy hub producing green hydrogen from biomass	Addresses various risk attitudes; integrates electrical energy storage for enhanced flexibility, Combines renewable sources with biomass-to-hydrogen technology; robust against multiple uncertainties	High computational complexity due to stochastic,	Multi-energy systems, demand uncertainty, energy storage integration, ensures robust decision making, electricity prices, renewable variabilities
Second-Order Stochastic Dominance (SSD) (Norouzi et al., 2024; Domínguez et al., 2024)	Selects solutions preferred by all risk-averse decision-makers	Ensures fair risk handling, less sensitive to specific probability values	Complex to implement, requires high-quality data	Multi-objective planning, investment under uncertainty, transmission lines expansion
Fuzzy Logic Methods (Unni et al., 2020, 2022)	Models vagueness or ambiguity using linguistic variables	Useful when data is imprecise, interpretable for expert systems	Less rigorous than probabilistic models, subjective rule definitions	Smart grid control, qualitative risk estimation, optimal energy mix estimation
Game Theory-Based Approaches (Tiwari and Singh, 2023, 2024; Tiwari et al., 2024; Yang et al., 2024; Fischer and Toffolo, 2024)	Manages risk sharing in multi-agent systems through cooperative or competitive models	Promotes fair resource allocation, reflects real-world stakeholder behavior	Complex equilibrium modeling; depends on accurate modeling of player incentives	Peer-to-peer energy trading, distributed grid risk coordination, interaction between utility and energy hubs, players

energy efficiency, cost-effectiveness and environmental performance (Ahmed et al., 2024). The model further integrates emerging technologies like electric vehicles (EVs), hydrogen systems, and seawater desalination units to boost operational flexibility (Ji et al., 2025). A two-stage stochastic optimization framework is implemented via GAMS and CPLEX, targeting multi-objective goals related to cost, emissions, and load balancing (Abbas et al., 2024). Demand Response Programs (DRPs) are included to dynamically manage electricity, gas, thermal, and water loads. In response to increasing variability from renewable energy sources, a day-ahead scheduling framework is developed using Monte Carlo simulations to account for uncertainties in solar irradiance, wind speed, and demand profiles. The integration of an e-fuel storage system further enhances system resilience, showcasing improved performance over conventional strategies (Alizadeh Aliabadi et al., 2025).

According to the literature, most of the works use stochastic optimization to address uncertainties and incorporate conditional value at risk (CVaR) for risk management. The detailed taxonomy of the recent literature highlighting algorithms used to address risk and uncertainties is shown in Table 3. Risk in energy systems primarily arises from the uncertainty in load demand and renewable generation, making real-time (RT) operation and scheduling increasingly complex. While techniques like CVaR and SSD help manage operational risks, limitations remain in accurately predicting extreme events and cascading failures. Despite significant progress in risk-aware energy system optimization, current models often rely on predefined scenarios or static uncertainty sets, limiting adaptability in real-time operations. Most existing methods do not fully capture dynamic risks arising from cyber-physical interdependencies or climate-induced volatility. Future research should focus on real-time, data-driven frameworks that integrate machine learning with risk modelling to improve resilience. Future research should also explore hybrid techniques that combine probabilistic, robust, and intelligent control methods for more adaptive risk mitigation in multi-energy systems.

9. Research gaps and future research directions

Based on the extensive and detailed literature review, the objective of this study is to highlight the key research gaps and how the current work could be extended, highlighting the future research directions to cover the research gaps and address advanced problems.

9.1. Key research gap

This section highlights the main research gap in the area of the multi-vectored networked energy hubs framework. To highlight the major shortcomings of the current literature, a tabular formulation is presented in this paper. Table 4 articulates a comparison of the literature based on the main resources, key objectives and technology types. Further, Table 5 highlights the detailed information on main energy management strategies, sources, and the key research gap points in the mentioned literature.

As mentioned, studies (Rezaei and Pezhmani, 2022; Alabdulwahab et al., 2015; Wang et al., 2018b; Comodi et al., 2017; Nazari-Heris et al., 2019; Gu et al., 2014; Zhang et al., 2014; Rehmani et al., 2018; Javadi et al., 2020; Jafari et al., 2020; Noorollahi et al., 2022; Dong et al., 2020; Rahgozar et al., 2022; Monemi Bidgoli et al., 2021; Cai et al., 2020; Daneshvar et al., 2020a; Eladl et al., 2020; El-Zonkoly, 2017; Shams et al., 2019; Najafi et al., 2021; Hou et al., 2020; Mirzapour-Kamanaj et al., 2020; Wu et al., 2018; Faraji et al., 2021) primarily focus on multi-vectored systems with different technology combinations, while aspects such as electric vehicle (EV) participation and explicit modelling of clustered or networked configurations are not central to their scope. To ensure flexibility, (Lekvan et al., 2021; Luo et al., 2020; Dabbagh-jamanesh et al., 2021; Nosratabadi et al., 2021; Li et al., 2018) investigate the role of EVs in multi-vectored systems; however, detailed representations of network topology, advanced energy storage integration, and coordinated multi-energy demand management are not the main focus in these works.

Literature (Mao et al., 2017; Kou et al., 2017; Zhao et al., 2018; Song et al., 2015; Wang et al., 2016; Liu et al., 2018a) discusses various topological structures of networked systems, mainly from an electrical perspective, with multi-energy system modelling only partially addressed. Similarly, (Anastasiadis et al., 2010; Nunna and Doolla, 2012; Nikmehr et al., 2017) analyze networked multi-microgrids for electrical systems; extending these ideas to fully multi-vectored architectures remains a promising research direction. Studies (Arnett et al., 2018; Saleh et al., 2016; Anastasiadis et al., 2010; Nunna and Doolla, 2012; Nikmehr et al., 2017; Misaghian et al., 2018; Hemmati et al., 2020; Mansouri et al., 2020; Nikzad and Samimi, 2021; An et al., 2018; Rezaei et al., 2022; Poursmaeil et al., 2021) investigate networked electrical systems and predominantly emphasize common network interests. Cooperative frameworks that simultaneously consider both collective objectives and individual interests of microgrids or energy hubs are relatively less explored and represent an opportunity for further work.

Literature (Daneshvar et al., 2020b, 2022a, 2020c; Liu et al., 2020; Khorasany et al., 2021a; Feng et al., 2020; Khorasany et al., 2021b; An et al., 2021; Jadidbonab et al., 2021) investigates the energy trading mechanisms in the multi-microgrid system. While references (Alsanousie et al., 2023; Chen et al., 2023, 2021; Zhang et al., 2023, 2022b; Limb et al., 2022; Moradi et al., 2022; Ma et al., 2021; Yuan et al., 2020; Xu et al., 2022, 2023; Yang et al., 2020, 2023; Fragiacomo and Genovese, 2020; Alizad et al., 2022; Zheng et al., 2023; Huang et al., 2022; Qian et al., 2020; Cheng et al., 2020; Wang et al., 2022; Wu and Li, 2023; Ju et al., 2022; Honarmand et al., 2021; Dolatabadi et al., 2017a) highlight the environmental benefits of carbon capture and storage (CCS), they overlook its economic impacts, including high operational costs. An emission market mechanism is needed to make CCS-integrated MVEHs economically and environmentally sustainable. Additionally, a comprehensive multi-objective study is required for MV-NEHs (heat-electricity-ice-hydrogen) to address economic, environmental, and reliability aspects, integrating multi-sectoral demands like industrial and transportation needs, EVs, demand response, and advanced energy storage systems such as compressed air and pumped hydro storage, and individual interests have not been explored in detail.

Moreover, the literature highlighted in Section 7 emphasizes the extensive application of IEEE test systems in multi-energy system integration, yet critical gaps remain. Many studies lack comprehensive integration of cooling and hydrogen systems, which limits the potential for sector coupling and operational flexibility. Furthermore, reliance on deterministic approaches for RES uncertainty modelling overlooks the dynamic and stochastic complexities of real-world conditions. Future research should focus on developing advanced frameworks that leverage the technical strengths of IEEE systems, incorporating hybrid energy vectors and advanced storage solutions. A notable gap is that most IEEE-based benchmark implementations still represent energy hubs as quasi-static injections and rarely embed multi-timescale coordinated control, explicit demand-side flexibility modelling, or game-theoretic incentive mechanisms within the coupled power–multi-energy network. These frameworks must optimize sector coupling across electricity, heating, cooling and hydrogen, while enhancing system resilience to address renewable variability and demand-side uncertainties. Based on this, future research direction is highlighted in the subsequent section.

9.2. Future research directions

Although detailed analysis has been explored in the areas of integrated energy systems, there are numerous areas where the development in this area could be done.

1. Advancing Multi-Energy System Operational Reliability: Existing research insufficiently addresses strategies to minimize renewable

Table 4
Review of different energy resources and technology in literature.

Ref. Attributes		(Lekvan et al., 2021)	(Noorollahi et al., 2022)	(Nosratabadi et al., 2021)	(Monemi Bidgoli et al., 2021)	(Amir Mansouri et al., 2021)	(Karimi and Jadid, 2021)	(Tan et al., 2021)	(Alizadeh Bidgoli and Ahmadian, 2022)	(Daneshvar et al., 2022a)	(Ju et al., 2022)	(Najafi et al., 2022)	(Zhou et al., 2018)	(Gupta and Gupta, 2015)	(Sharma et al., 2021)	(Shams et al.)
Architecture (Single (S) or Networked (N))		S	S	S	S	S	N	N	N	N	N	N	N	N	N	N
Multi-vectored system	Electrical	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Heat	✓	✓	✓	✓	✓	–	–	–	✓	✓	✓	✓	–	✓	✓
	Cool	–	✓	–	✓	✓	–	–	–	–	–	–	✓	–	✓	–
Demand Response (DR)	e-DR	✓	–	✓	✓	–	✓	✓	–	–	✓	–	–	–	–	–
	h-DR	–	–	✓	–	–	–	–	–	–	–	–	–	✓	–	–
	c-DR	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Resources	Grid	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Local DG	–	–	–	–	–	✓	✓	–	–	–	–	–	–	✓	–
	RES	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓
	CHPs	✓	✓	✓	✓	✓	–	–	–	–	✓	✓	✓	–	✓	✓
	Boiler	✓	–	✓	✓	✓	–	–	–	–	–	✓	✓	–	✓	✓
	Heat pumps	–	✓		✓	✓	–	–	–	–	✓	–	–	–	–	✓
	e-chiller	–	–	–	–	✓	–	–	–	–	–	–	✓	–	✓	–
	AC	–	✓	–	✓	✓	–	–	–	–	–	–	✓	–	✓	–
RES Stochasticity		✓	✓	✓	✓	–	✓	–	✓	✓	–	✓	✓	–	✓	✓
Energy Storages (ES)	e-ESU	✓	–	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓
	h-ESU	✓	✓	✓	✓	✓		–	–	✓	–	–	✓	–	✓	✓
	c-ESU	–	–	–	–	✓	–	–	–	–	–	–	–	–	✓	✓
	CAES	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
	PHS	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Hydrogen	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–
Plug-in Electric Vehicles (PEV)		–	–	✓	–	✓	–	–	–	–	–	–	–	–	–	✓
Power-to-X		–	✓	–	–	–	–	–	–	✓	✓	✓	–	–	–	–
Local Energy sharing among hubs		–	–	–	–	✓	–	✓	–	✓	–	✓	✓	–	✓	–
Emission Market		–	–	–	–	–	–	–	–	–	✓	✓	–	–	✓	–
Multi-Objective		–	–	–	✓	–	✓	–	–	–	–	–	✓	–	✓	✓
RES Curtailment		–	–	–	–	–	–	–	–	–	✓	–	✓	✓	–	✓
Collective Network Interest	Cost	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	EM	–	–	✓	✓	–	✓	–	–	–	–	–	–	–	✓	–
	Reliability	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–
Individual Interests of Participants in Network Architecture		–	–	–	–	–	✓	–	✓	–	–	✓	–	✓	✓	–

Table 5
Comparison of important literature and current research work.

Ref.	Key Features	Specific Attributes	Limitations
(Karimi and Jadid, 2019)	Multi-objective optimization for cost, ENS, and ESS maximization.	Develops a detailed optimization framework capturing ESS charge–discharge dynamics under multi-timescale electricity prices.	EV participation, multi-carrier MG frameworks, and explicit emissions analysis are not modelled.
(Misaghian et al., 2018)	Tri-level optimization addressing unit commitment and MG-grid coordination.	Investigates cost minimization and Models multiple energy carriers within an energy hub, enabling explicit evaluation of cross-vector interactions.	EVs, DR, MG power flow, and emissions impact are not considered.
(Chen and Zhu, 2017)	Deterministic, non-cooperative model integrating RES.	Provides mathematically equilibrium conditions suitable for analyzing competitive behaviour under varying RES availability.	RES uncertainties, demand response, and multi-carrier interactions are not explicitly represented.
(Xie et al., 2018)	Competition-based optimization for networked MGs with technical constraints.	Models transmission parameters and networked MG interactions; Demonstrates improved reliability and reduced feeder congestion through coordinated local generation.	Lacks EVs, DR, emissions analysis, and fair pricing among MGs.
(Jalali et al., 2017)	Bi-level strategic game framework for DSO-MG cost minimization.	Captures hierarchical interaction between DSO and MG using a bi-level decision structure reflecting real-world operational coupling and MG power exchange.	Excludes EVs, DR, and multi-carrier systems.
(Nasiri et al., 2020)	Stochastic bi-level optimization for RES uncertainties and multi-carrier hubs.	Addresses RES uncertainties; Demonstrates robust system balancing by leveraging BESS coordination under uncertain RES output.	EVs, demand response, and explicit emissions evaluation are not considered.
(Fang and Yang.)	Cooperative MST-based optimization for MG topologies and critical load allocation.	Reduces power loss and provides insights into cooperative MG scheduling and critical-load allocation under varying topology configurations.	EVs, DR, and multi-carrier systems are not considered.
(Bui et al., 2018)	Hierarchical energy management with community storage integration.	Includes RES uncertainty within a distributed EMS framework, enabling robust DR and BESS coordination.	Excludes RES uncertainties, EVs, and MG fair price allocation.
(Fan et al., 2018)	Cooperative energy management for multi-carrier hubs with power exchange.	Models coupled thermal–electrical flows within multi-carrier hubs to improve flexibility and system efficiency.	Lacks RES uncertainties, DR, EVs, and emissions evaluation.
(Daneshvar et al., 2020c)	Chance-constrained programming for RES uncertainties and hub interactions.	Investigates power exchange and captures key multi-vector interactions, enabling risk-informed scheduling across coupled energy carriers.	Excludes DR, EVs, and emissions analysis.
(Bahmani et al., 2021)	Cooperative multi-carrier hub optimization with DR integration.	Incorporates DR within multi-carrier hub operations and applies a structured cooperative payoff allocation mechanism.	Excludes RES uncertainties, EVs, and emissions analysis.
(Tostado-Véliz et al., 2022)	Cooperative energy management with stochastic optimization for prosumers.	Models EV behaviour, storage systems, and controllable devices within a stochastic prosumer-level framework.	Lacks multi-energy systems, RES curtailment penalties, DER rewards, and system reliability analysis.
(Vahid Pakdel et al., 2020)	Deterministic multi-carrier energy management addressing the energy-water nexus.	Models the interdependency between energy and water sectors within an integrated multi-carrier dispatch framework.	Omits RES uncertainties, DR, and EV integration.
(Hakimi et al., 2021)	Stochastic optimization integrating EV behaviour with RES uncertainties.	Integrates renewable variability with multi-stage decision-making for improved scheduling fidelity.	Lacks multi-carrier systems, emissions evaluation, and DR.
(Jani et al., 2021)	Two-level stochastic energy management for MG surplus and deficiencies.	Considers surplus/deficiency conditions with two-level stochastic optimization incorporating price-based DR.	Excludes multi-carrier systems, EVs, and emissions impact.
(Khavari et al., 2020)	Deterministic bi-level power management with Shapley value-based fair allocation.	Addresses congestion management at PCC through a bi-level power management structure.	Omits multi-carrier systems, RES uncertainties, and DR integration.
(Jafari et al., 2020)	Stochastic multi-objective optimization for single MGs.	Employs stochastic multi-objective optimization to incorporate ENS, DR, and cost objectives.	EV integration, RES curtailment penalties, and the networked system are not discussed.
(Nasir et al., 2022)	IGDT-based energy management for multi-energy hubs.	Integrates electrical, thermal, and hydrogen storage into a unified IGDT-based uncertainty framework.	EVs, RES curtailment penalties, and DER reward mechanisms are not considered.
(Karimi et al., 2021)	Stochastic multi-objective optimization for MG independence and cost reduction.	Models MG independence and incorporates DR into cost–reliability trade-offs under renewable uncertainty.	Lacks RES curtailment penalties, EVs, and multi-carrier systems.
(Liu et al., 2018b)	Robust stochastic optimization using Stackelberg game for energy trading.	Incorporates RES uncertainties and demonstrates the benefits of coordinated scheduling across	Neglects multi-carrier systems, fair pricing, and emissions evaluation

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Table 5 (*continued*)

Ref.	Key Features	Specific Attributes	Limitations
		interconnected MG clusters.	
(Salehi et al., 2019)	Stochastic multi-carrier energy hub optimization for cost and emissions.	Includes EVs and BES integration Integrates DR with heat–electric exchange in multi-vector MG operations.	Excludes cooling loads, RES curtailment penalties, and cooperative payoff allocation.
(Daneshvar et al., 2020b)	Stochastic transactive energy management for MGs.	Investigate RES uncertainties and energy exchange, and capture RES uncertainty and market-driven flexibility through a value-based dispatch structure.	Omits DR, EVs, and fair payoff allocation.
(Hwang Goh et al., 2022)	Stochastic optimization using quantum particle swarm for low-energy systems.	Integrates demand response and develops robust cooperative optimization for integrated hubs under uncertain supply–demand conditions.	Excludes multi-energy systems, EVs, advanced storage, power-to-gas, CCS-U, and networked frameworks.
(Zhao et al., 2020)	Stochastic approach for multi-carrier MGs with day-ahead bidding.	Includes thermal, ice storage, and Addresses uncertainty propagation across interacting hubs under variable RES output.	DR, EVs, and networked systems are not explicitly represented.
(Fambri et al., 2022)	Deterministic optimization for low-emission multi-energy systems with P2G.	Investigate Power-to-X units to ensure the optimal usage of RES in the single energy hub concept. Electrical and gas network parameters are included.	Excludes EVs, advanced storage, CCS-U, uncertainties and networked frameworks.
(Rezaei et al., 2022)	Risk-constrained stochastic approach for multi-carrier MGs.	Investigates emissions and Models MG interactions using hierarchical control, incorporating DR and RES variability.	Omits cooling loads, DR, and fair price allocation.
(Zare Oskouei et al., 2021)	Stochastic multi-energy hubs with wind curtailment and emissions analysis.	Models uncertainty and proposes a coordinated scheduling framework for MG clusters under renewable uncertainty.	Excludes EVs, ice storage, and networked hub independence
(Poursmaeil et al., 2021)	Robust optimization for multi-carrier hubs with RES uncertainties.	Considers DR and heat-electric exchange Analyses demand flexibility and local generation to reduce operational costs.	Lacks advanced EV modelling and thermal DR
(Khorasany et al., 2021b)	Stochastic transactive energy framework for multi-energy hubs.	Models cost-emission tradeoffs and market-based local energy exchanges	Omits EVs, DR, and MG independence analysis
(Sarlak et al., 2022)	Stochastic modelling of RES uncertainties in multi-energy systems.	Incorporates hydrogen storage, electrolyzers, and demand response. Probability density functions are incorporated to model uncertainties of RES.	Excludes EVs, advanced storage, CCS-U, and networked frameworks.
(Liu, 2023)	Stochastic optimization with CCS-U integration for low-emission systems.	Analyses incentive-based DR participation in emission-constrained operation. Models CCS-U integration within a stochastic low-emission energy system.	Lacks networked frameworks, advanced storage, and detailed emission market mechanisms.
(Dong et al., 2020)	Stochastic single-objective optimization for peak energy supply management.	Develop a virtual power plant concept by coordinating wind, solar, and pumped hydro power; model wind and solar variability to reflect realistic renewable conditions.	Excludes DR, EVs, and networked systems.
(Rezaei and Pezhmani, 2022)	Stochastic optimization for multi-MGs with P2H technology.	Develop a multi-microgrid architecture with a focus on modelling tie-line contingencies. Integrates DR to enhance resilience under fluctuating thermal–electric demands.	Omits EVs, networked MG independency, and fair pricing
(Zhong et al., 2022)	Stochastic optimization for multi-energy MGs with RES curtailment mitigation.	Develops stochastic optimization, including RES curtailment mitigation and energy sharing among hubs	Excludes advanced storage, EVs, and fair pricing mechanisms
(Rahgozar et al., 2022)	Stochastic optimization for single energy hubs with resiliency studies.	Integrates DR and storage systems Conducts resiliency analysis for single hubs under uncertainty using stochastic optimization	Lacks networked systems, ice storage, and advanced EV modelling
(Daneshvar et al., 2021b)	IGDT-based stochastic energy management for industrial MGs.	Applies IGDT for industrial MGs, capturing uncertainty in load and RES availability. Develop a local energy trading market to ensure the economical operation of the multi-microgrid concept.	Omits EVs, RES curtailment penalties, and reliability.
(Daneshvar et al., 2022b)	CVaR-based risk assessment for multi-energy MGs.	Addresses techno-economic-environmental challenges. Captures decision-maker risk preferences in multi-energy MGs.	Excludes EVs, fair pricing, and reliability concerns.
(Luo et al., 2019)	Deterministic cooperative energy management for	Model networked architecture to smartly use excess energy. Implements Shapley-value-based	RES uncertainties, advanced payoff models, and

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Table 5 (*continued*)

Ref.	Key Features	Specific Attributes	Limitations
	multi-energy MGs.	fair cost allocation for multi-energy hubs	heating networks are out of scope.
(Mansour-Saatloo et al., 2020)	Stochastic robust optimization for multi-energy systems with hydrogen markets.	Considers multiple storage and DR integration Designs stochastic robust optimization integrating hydrogen markets and multiple storage types.	Excludes EVs, emissions reliability, and RES curtailment penalties.
(Ahmarinejad, 2021)	Multi-objective MILP for 20-year MG planning.	Integrates DR and storage units Develops a multi-objective MILP for long-term MG planning, incorporating DR and storage	Lacks EVs, RES curtailment penalties, and reliability analysis
(Salyani et al., 2023)	Deterministic strategy for MGs in normal and resilient modes.	Design a multi-microgrid architecture with DR and energy storage units. Develop a hybrid cooperative-competitive strategy to ensure the individual interests of MGs.	Excludes advanced EV modelling and RES curtailment mechanisms
(Talari et al., 2022)	Transactive energy mechanism with Bayesian Nash theory.	Supports individual MG interests in cooperative trading. Implements a Bayesian Nash-based transactive market mechanism enabling cooperative MG trading	Ignores EVs, advanced storage, and emissions penalties
(Wu and Li, 2023)	Distributed optimization for hybrid power-to-gas systems.	Integrates CCS-U and carbon markets within a hybrid P2G-oriented distributed optimization	Ignores DR, reliability, and advanced storage
(Ikäheimo et al., 2022)	Deterministic optimization for Nordic MG systems with direct air capture.	Evaluates DAC vs. post-combustion CCS Provides deterministic techno-economic comparisons across carbon removal pathways	Excludes RES uncertainties, advanced EV modelling, and storage systems like CAES
(Ma et al., 2021)	Deterministic modelling of MG systems with P2G and CCS.	Captures carbon trading interactions and evaluates techno-economic system benefits	Lacks RES uncertainties, advanced storage, and DR integration

energy curtailment and maximize the utilization of stationary and mobile energy storage systems, such as electric vehicles (EVs). Future studies should focus on frameworks that enhance network self-reliability while aligning with regional and holistic energy goals.

2. Game-Theoretic Frameworks for Coalition Profit Distribution: Effective profit allocation within coalitions of Multi-Vectored Energy Hubs (MVEHs) remains underexplored. Current methods, such as the Shapley and Nucleolus approaches, fail to fully consider the specific traits and contributions of individual hubs. Future research should develop advanced game-theory-based mechanisms that:

a. Ensure Equity: Allocate profits impartially, rewarding hubs based on their distinct capabilities and contributions.
b. Incorporate Renewable Energy Variability: Recognize the financial risks posed by unpredictable renewable energy sources (RESs). Penalty-reward schemes should penalize hubs for underperforming RES generation while rewarding them for emission-free and sustainable contributions.
c. Align Collective and Individual Goals: Balance network-wide objectives, such as emission reductions and energy security, with the unique interests of each hub in the coalition.
d. Promote Network Resilience: Foster cooperation by ensuring fair payoff distributions that incentivize resource sharing and mutual support during critical operational scenarios.

These mechanisms would advance the economic and operational stability of MVEHs, ensuring a resilient and sustainable networked energy system.

3. Currently, AI and ML applications in multi-energy systems predominantly focus on renewable energy forecasting, such as solar and wind resource predictions. However, their integration into other sectors, including optimized network design, energy storage efficiency enhancement, trading mechanism and dynamic demand-supply management, is still limited. Future research should explore:

a. Optimized Network Design: AI-driven frameworks can analyze large datasets to identify optimal energy network topologies, improving system efficiency and reducing transmission losses through adaptive and automated network configuration for dynamic energy demands.
b. Energy Storage Efficiency: AI optimizes the management of diverse energy storage systems, including thermal, electrical, hydrogen, and hybrid storage. For thermal storage, AI predicts and regulates energy flow in district heating/cooling systems to minimize waste. In electrical storage, machine learning enhances charging/discharging cycles through demand forecasting, extending battery life. Hydrogen storage benefits from AI-driven optimization of production and utilization during surplus renewable energy periods. Hybrid storage systems are dynamically coordinated using AI to maximize efficiency and lifespan. Through real-time analytics and predictive controls, AI ensures seamless integration of storage systems into multi-energy networks, enhancing reliability, reducing costs, and improving system performance.
c. Multi-Vector System Integration: Utilizing AI to model interactions among diverse energy vectors (electricity, gas, hydrogen, etc.), enabling coordinated and adaptive control. AI-driven models can simulate and manage interactions among energy vectors, such as electricity, gas, and hydrogen, ensuring coordinated operation, real-time energy exchange, and adaptive control for system reliability. This could also help predict the efficient usage pattern of different energy vectors and error detection at integration nodes.
d. AI-driven energy trading: AI can enable high-speed coalition formation among neighbouring Multi-Vectored Energy Hubs (MVEHs) and develop adaptive energy trading models for retail markets. Neural networks can estimate the cooperative and non-cooperative behaviour of market participants with high accuracy. These models can adapt to network changes or an increasing number of agents, providing cost-effective and reliable energy scheduling. AI can also automate trading strategies to optimize energy distribution and reduce market inefficiencies.

10. Conclusion

Multi-vectored energy hubs (MVEHs) and their networked extensions (MV-NEHs) offer an integrative framework to cooperate electricity, heating, cooling, hydrogen, and other energy carriers under a unified operational architecture. By enabling cross-vector flexibility and enhancing renewable integration, they are foundational for building resilient, low-emission energy systems. This paper provides a comprehensive review of MVEH architectures, novel game-theoretic energy management strategies, and advancements in low-emission and flexible technologies such as Power-to-X, with a distinctive emphasis on their interaction with power system constraints using IEEE and other benchmark test grids.

A scientometric analysis highlights global research evolution and key contributors, while the review systematically articulates diverse network architectures, transactive and cooperative energy exchange mechanisms, and temporal coordination strategies. This study develops a detailed comparison across multi-timescale coordinated control (day-ahead, intraday, real-time, planning), centralized and decentralized management schemes, while showcasing the interaction of multi-energy vectors in the power system, especially in IEEE benchmarks, providing a systematic representation of existing integrated frameworks and their operational characteristics. Further, the review also discusses the interdependencies of multiple energy flows and their associated uncertainties and risks that arise due to complex interconnections. The extended review of objective functions, coupling constraints, flexibility representations, assumptions and solver platforms provides a comparative foundation for future modelling standardization and system scalability.

The main conclusive points of this research work are:

- IEEE test systems remain essential modelling backbones, with IEEE-33 bus being most widely used for representing electricity–thermal–gas integration, while 118/123 bus systems offer scalability assessments for sector coupling, hydrogen trading, and resilience studies.
- Flexibility technologies such as electric storage, CHP, heat pumps, demand response, and Power-to-X units are increasingly incorporated; however, their operational coordination remains predominantly confined to single-layer or day-ahead scheduling, with limited integration across multi-timescale and cross-vector planning frameworks.
- Operational modelling efforts predominantly emphasize short-term day-ahead scheduling, often using stochastic, CVaR, or IGDT-based formulations to address mainly renewable variability. However, most approaches rely on static uncertainty sets, with limited integration across real-time dispatch, near-term flexibility allocation, and long-term investment planning. The dynamic propagation of uncertainty, adaptive risk management, and modelling of extreme events, including cyber-physical disruptions, remain underexplored.
- Critical sectoral couplings such as demand-side flexibility, P2G conversion, hydrogen storage, and cooling integration remain underrepresented, underscoring the need for deep sectoral integration and co-optimization approaches that capture interdependencies across energy carriers, spatial scales, and planning horizons.

The findings underscore that future research must strengthen hybrid coordination frameworks that integrate robust optimization that includes modelling of extreme events and distributed cooperative–competitive mechanisms, with multi-layer governance planning through System of Systems approach (SoS). Emphasis should be placed on aligning planning and operational decisions across temporal hierarchies and energy vectors, particularly through coordinated day-ahead and real-time control layers.

While current studies predominantly focus on forecasting applications, the application of AI in multi-energy system architecture, real-time topology control, predictive flow management, cross-vector demand–supply balancing for improved peer-to-peer trading under sector-coupled constraints remains limited. The role of game-theoretic coalition mechanisms also requires further investigation to ensure equitable payoff distribution among all players (i.e., energy vectors or hubs), accounting for renewable variability, emission-based incentives, and operational resilience. Standardizing modelling assumptions, including solver platforms, objective functions, coupling metrics, and temporal resolution, is essential to improve reproducibility and cross-comparison. Expanding IEEE-based benchmarks to explicitly capture inter-hub interactions, cooperative market coordination, and cooling network integration under deep uncertainty will be critical to developing scalable, low-emission benchmarked energy systems.

Author statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process. He/she is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

CRediT authorship contribution statement

Shubham Tiwari: Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Hamid Karimi:** Writing – review & editing, Data curation. **Milad Rahimipour Behbahani:** Writing – review & editing, Data curation. **Ankit Garg:** Writing – review & editing, Data curation. **Jai Govind Singh:** Writing – review & editing, Data curation. **Sidharath Joshi:** Writing – review & editing, Data curation. **Kraxner FLorian:** Writing – review & editing, Supervision. **Fabian Schipfer:** Writing – review & editing, Data curation.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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