Energy and Climate Management, 2025, 1(2): 9400004
https://doi.org/10.26599/ECM.2024.9400004

Review

Complex network modeling for energy and carbon emission systems: Current status and prospects

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Received: 23 November 2023; Revised: 26 January 2024; Accepted: 29 March 2024

ABSTRACT

In the context of climate change and energy security, the investigation of energy and carbon emission systems serves as a scientific foundation for nations to devise sustainable development strategies. Complex network models have gained significant attention in the academic community due to their ability to effectively capture intricate connections and dynamic processes. However, the applicability and interpretability of complex network modeling techniques must be fully utilized based on a deep understanding. The objective of this study is to provide a comprehensive overview of the application of complex network models within energy and carbon emission systems. To achieve this, the paper first introduces the theoretical basis. Then, the progress of complex network model application in the field of energy and carbon emissions is examined. By employing keyword co-occurrence and literature co-citation analysis, the trends and hotspots in this field are explored. Most importantly, we provided an example of renewable energy trade to illustrate the application of network modeling. This example showcases how network modeling can be applied to analyze and understand the dynamics of renewable energy trade. Lastly, the paper outlines future research directions and challenges from the perspectives of index interpretation, multi-agent modeling, and the combination of multiple methodologies. In conclusion, this research offers comprehensive insights for stakeholders interested in the application of complex network modeling in related fields.

KEYWORDS

Energy, carbon emissions, complex network, applicability, limitations, future frontiers.

1 Introduction

In the face of the dual challenges of climate change and energy security, conducting in-depth research on energy and carbon emission (E&C) systems has become a crucial endeavor for nations to address environmental issues and promote sustainable development. The system of E&C is highly interconnected and intricate that encompasses various levels and domains, exhibiting significant spatial and temporal variations. Consequently, analyzing the complex and intricate relationships within this system poses significant challenges. Fortunately, complex network theory (CNT) offers a promising approach to gaining a deeper understanding of the inherent mechanisms and evolutionary patterns of E&C systems. CNT is highly practical for modeling both independent and interdependent complex systems. In recent years, the research on CNT and its applications has significantly proliferated, resulting in a substantial number of articles being published in prestigious international journals such as Science, Nature, and PNAS[1–3]. This growing body of literature reflects the increasing recognition of CNT as an emerging and impactful research hotspot in academia. Scholars have enthusiastically applied this innovative theoretical tool to investigate various large and intricate real-world systems. Among these systems, the structure of E&C systems and the relationship between structure and function have emerged as particularly compelling and widely explored topics of interest for scholars.

Network modeling of E&C systems involves modeling and analyzing each participant and their relationships. This approach provides valuable insights into the structure, operation, and internal mechanisms of a system. The practical application of network modeling in the field of E&C has encompassed various aspects. For instance, the development of a network model for embodied energy systems allows for the analysis and optimization of energy flow and distribution[4]. By constructing network models of direct or indirect carbon emissions among sectors, cities, or countries, the transmission and accumulation of carbon emissions can be deposited[5]. Moreover, employing network evolution enables the analysis of the structure and dynamics of the energy market, facilitating resource allocation optimization. Furthermore, it is possible to identify weak links in the energy system, predict potential failures, and enhance resilience against risks[6].

Currently, complex network modeling techniques have found extensive applications in various domains, such as energy system optimization, carbon price analysis, energy market risk management, and failure prediction. Despite the numerous studies exploring complex network modeling in the field of E&C, there is a lack of systematic and comprehensive research reviews on its application. To effectively showcase the research advancements in this field, we employed bibliometrics to visualize the existing literature[7]. We conducted a search in the Web of Science Core Collection using the query preview TS = (“Carbon emission” OR “Fossil energy” OR “Renewable energy” OR “Coal” OR “Gas” OR “Oil”) AND TS = (“Complex network” OR “Social network analysis”). The search was limited to the period from 2000 to 2023. To ensure language consistency, we focused on

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 https://doi.org/10.26599/ECM.2024.9400004

English-language publications. We selectively considered document types classified as “Article” or “Review Article”. To refine the dataset, we excluded entries classified as “Book Chapters,” “Early Access,” and “Proceedings Papers”. Finally, a total of 859 articles were selected for analysis.

Figure 1 illustrates the number of publications from 2000 to 2023. As depicted in the graph, the literature in this field has experienced rapid growth since 2000, with an average growth rate of 37%. Particularly, after 2008, the average annual growth rate has increased to 42%. This indicates that the complex network method is intricately linked to the implementation of environmentally friendly and low-carbon development, sustainable development, and energy transition in the context of global energy security and climate change. Furthermore, it highlights the importance of integrating scientific methodologies with practical problems to effectively address society’s pressing needs in resolving energy and environmental challenges.

It is worth mentioning that there are several shortcomings and challenges that warrant attention in this field. From a fundamental perspective, there is a need to explore various aspects during the modeling process. This include, but are not limited to, determining what kind of data is suitable for building a network model, developing appropriate methods for constructing network models, identifying the main research hotspots and trends in the field, and correctly interpreting the results obtained from network metrics. Addressing these questions is crucial for gaining a better understanding of the phenomena observed in complex systems using this interdisciplinary tool.

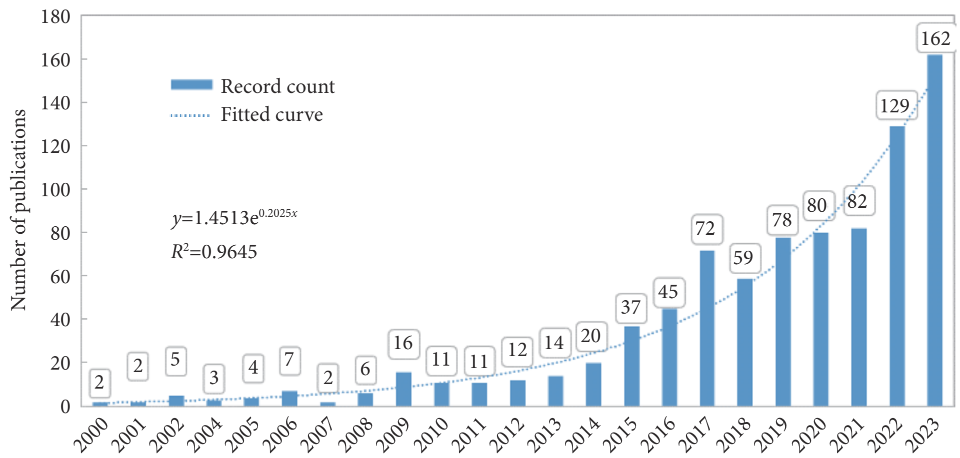

Fig. 1 The number of publications during 2000–2023.

The remainder of the paper is organized as follows. Section 2 provides a brief introduction to complex network theory. Section 3 utilizes keyword and citation analysis to showcase the primary applications of complex network modeling techniques in the field of E&C systems. Section 4 provides an illustrative example. Section 5 provides possible limitations and potential outlooks. Finally, Section 6 concludes the work.

2 Complex network theory

In the current empirical research literature related to energy and carbon emissions, CNT is also commonly referred to as social network theory (SNA). This is because the existing empirical research in this field is extensively involves social actors. It aims to establish connections among actors that may not be linked in the social context. SNT and CNT are two related but distinct fields of study. SNA is a field of study that examines the patterns of relationships and interactions between individuals, groups, organizations, or any other entities in a social system. On the other hand, CNT is a broader field that studies the structure and dynamics of complex systems composed of interconnected elements. It encompasses various types of networks, including social networks, biological networks, technological networks, and more. CNT focuses on the properties and behavior of these networks as a whole, rather than specifically emphasizing social relationships. Complex network modeling offers a powerful framework for understanding and analyzing complex systems, enabling predictions, identifying critical elements, and informing decision-making processes across various disciplines (see Figure 2).

From a mathematical perspective, a network can be represented as a graph composed of a group of independent nodes and

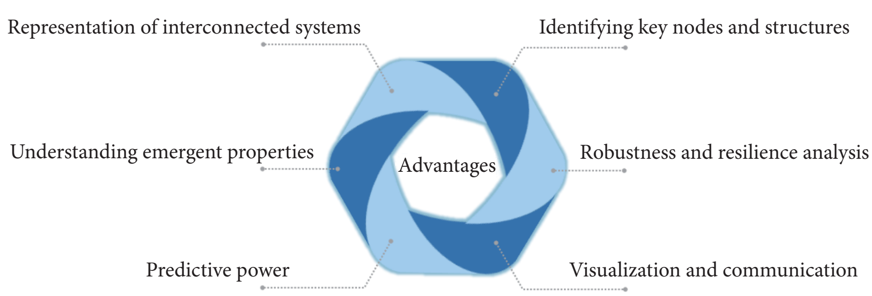

Fig. 2 Six advantages of complex network modelling.

complex connected edges between them. It is denoted as $G=(V,E)$, where $V=\{v_1,v_2,\cdots,v_N\}$ represents the set of nodes in the network, and $E=\{e_1,e_2,\cdots,e_m\}$ represents the set of edges connecting the nodes. Therefore, the definition of many network indicators is derived from graph theory[8]. Let $A=\{a_{ij}\}$ be the adjacency matrix of graph G. If the edges connecting node i and node j has a specific direction, it is referred to as a directed edge; otherwise, it is an undirected edge. A network composed of directed edges is known as a directed network (see Figures 3(a) and 3(b)), while a network composed of undirected edges is called an undirected network (see Figures 3(c) and 3(d)). Furthermore, if the edges in the network are without weights, the graph G is an unweighted network (as shown in Figures 3(a) and 3(c)). Conversely, if the edges have associated weights, the graph G is a weighted network (as shown in Figures 3(b) and 3(d)). In a weighted network, the weight between any two connected nodes may vary, and this weight is referred to as the edge weight. The specific modeling steps are explained in Figure 4.

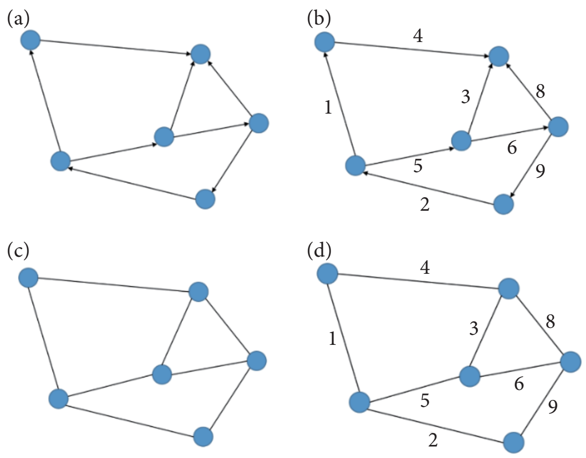

Fig. 3 A sample of different kinds of networks.

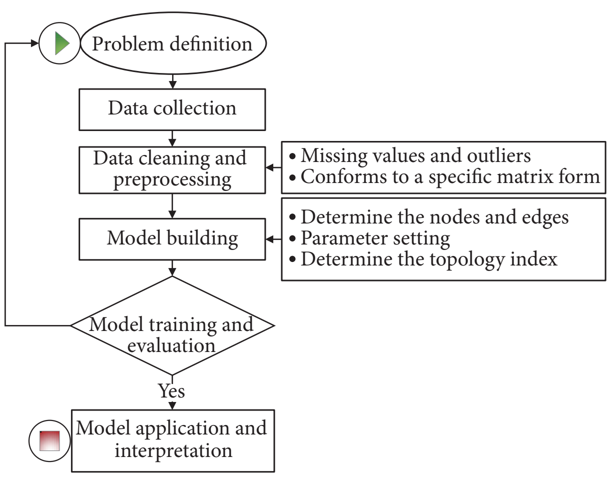

Fig. 4 The flow chart of complex network modeling steps.

3 Historical trends and hotpots analysis

Figure 5 illustrates the temporal distribution of the keyword co-occurrence map derived from 859 articles published between 2000 and 2023. This map consists of 638 nodes and 1,829 edges. Figure 5 displays the evolving relationships among keywords over time. The map enables researchers to gain insights into the progression of research topics, connections between keywords, and changing focuses within the field of E&C throughout the years. It is evident that during the initial years, keywords such as "evolution," "model," and "complex network" frequently co-occurred, indicating a focus on dynamic solutions. However, recent years have witnessed emerging associations between keywords like "spatial network," "vulnerability," "supply chain," and "systemic risk," suggesting increasing emphasis on comprehensive strategies rather than presenting straightforward outcomes. Moreover, around 2017, there was a surge of interest in analyzing prices, particularly oil prices, and examining the embodied energy along with trade.

3.1 Evolutionary analysis under various topics

Drawing on the insights derived from Figure 5, this paper classifies the keywords into three main research topics: price, energy/carbon footprint, and supply chain network.

First, the relevant keywords for price system include "time series," "oil price," "identification," "pattern," and others. Various modeling techniques have been employed for energy and carbon prices, such as visibility graphs (VGs), horizontal VGs, limited penetrable visibility graphs (LPVGs), Pearson correlation coefficients, Rank-order correlation coefficients, and so on[9, 10]. Existing research demonstrates that complex network modeling techniques have significant potential in revealing return volatility of individual prices, spillover mechanisms between different price markets, the risk of price shocks from unexpected events, and predicting market trends[11–13]. For example, in the energy and carbon financial markets, a price correlation network can be established to examine the strength of correlations between different assets. By analyzing the network's evolution, market trends and potential price fluctuations can be predicted. However, many economists still struggle to grasp the practical interpretation of time-series network models such as VGs, and a deeper explanation is needed for the statement that "structure determines function." Additionally, from a methodological perspective, single-sequence symbolic network models may not be suitable for capturing the interdependence among multiple energy products in a price linkage system. Therefore, further exploration is warranted in applying coarse-grained multilayer systems[14] to analyze the linkage between energy prices, carbon prices, and economic prices.

Second, the relevant keywords for energy and carbon footprint include "footprint," "multi-regional input–output model," and others. The study of direct and indirect energy and carbon emissions during commodity flows has attracted significant attention globally, particularly in developing countries. Scholars have examined fossil fuels, renewables, electricity, and carbon emissions embodied in commodity trade using input–output models and life cycle assessments. The environment-extended single- or multi-regional input–output model (EESRIO or EEMRIO) is widely recognized as the approach of choice, and many countries have disclosed their input–output tables. Numerous scholars have utilized this model to analyze the flow of embodied energy and carbon emissions across countries[15–16], regions[17, 18], cities, and sectors[19]. Moreover, an increasing number of authors have employed complex network analysis to visualize the results. For example, Gao et al., (2015)[4] constructed the international fossil energy trade multilayer network (ETMN) and examined its evolutionary characteristics by generalizing several

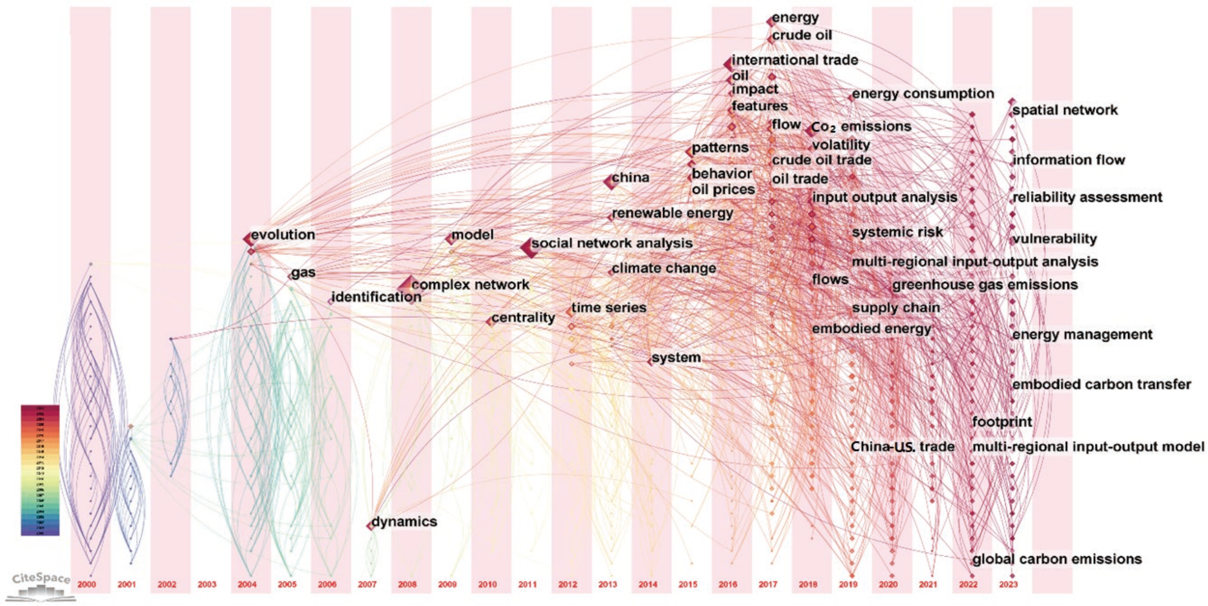

Fig. 5 Keywords co-occurrence temporal map. Notes: This figure was generated by the authors using CiteSpace software (version 6.2). The size of each node represents the frequency of keyword occurrences, while different time zones indicate when the keywords appeared.

indicators such as degree distribution, community structure, community stability, and the time-varying evolution of key countries' importance. Wei et al., (2020)[20] further investigated the transfer of electricity-related carbon emissions and value-added in China's inter-provincial trade using social network analysis. Gao et al., (2023)[21] examined the coopetition relations in terms of renewable energy trade among Belt and Road Initiative (BRI) countries by constructing a two-layer network model. These studies have demonstrated the practicality and unique insights provided by complex network analysis in this field.

Third, the relevant keywords for supply chain network include "international trade," "crude oil trade," "supply chain," "flows," "China–U.S. trade," and others. The supply chain network involves constructing a network that captures the interactions between each link in the supply chain and their relationships. The resulting network is often multi-layered or colored, with the coloring the nodes or edges facilitating the distinction of their attributes. This enables the identification of key nodes and weak links in the supply chain network. Nodes can represent suppliers, manufacturers, distributors, and retailers, while the network's edges represent the logistics, information flow, and capital flow between them[22]. However, the application of supply chain networks in the E&C system is currently limited. Nonetheless, supply chain networks have attracted significant attention since 2021, likely due to the complex nature of supply chains in a globalized economy and their critical role in business success. In the future, supply chain networks can reveal various mechanisms, including structural analysis and supply process optimization[23], risk management and vulnerability assessment[24, 25], resilience in the face of shocks such as natural disasters and market volatility[26–28], cooperation mechanisms among different participants[29], and environmental impact[30].

3.2 Hotspots based on co-citation analysis

To reveal the research trends in the field of complex networks and identify current research hotspots, this paper employed Citespace software to conduct a co-citation analysis of the 859 articles. Figure 6 depicts the changes in research hotspots through color variations. Additionally, a clustering analysis was conducted on the co-citation network (see Figure 7), with cluster labels derived from the titles of the citing literature. Two primary research hotspots were identified and Table 1 presents the top 5 most cited articles in each cluster.

Cluster 0, the largest cluster comprising 164 papers, primarily focuses on the combined use of input–output analysis and complex network models to study greenhouse gas emissions in trade flows[31–33], energy flows[34, 35], and regional space[36, 37]. Complex network models in this cluster enable the quantification of the structure and evolution of carbon emission transfers.

Cluster 1, consisting of 111 papers, centers around pattern recognition, causal relationship recognition, and feature extraction of time series data using complex network models[38–42]. It also explores the identification of community structures and evolutionary mechanisms in trade networks[43]. Complex network models in this cluster enable the analysis of internal relationships and interactions within a system, unveiling information propagation and evolutionary mechanisms.

4 IllustraTive example: Renewable energy trade along the BRI countries

4.1 Network construction

The practical implementation of network modeling techniques necessitates a set of general steps and fundamental principles. This paper employs the case of renewable energy trade among countries participating in the BRI to demonstrate the process of modeling complex networks. The first and foremost step is to assess the suitability of the data. Typically, graphs are represented in the form of matrix data. The initial step of constructing a network is accomplished when the objects being studied can be represented as data in matrix form. In our illustrative example, we consider four types of renewable energy products: solar, wind, hydro, and biomass, encompassing 66 countries. A matric can be generated based on the data obtained from the United Nations Comtrade Database. In the illustrative example, countries are

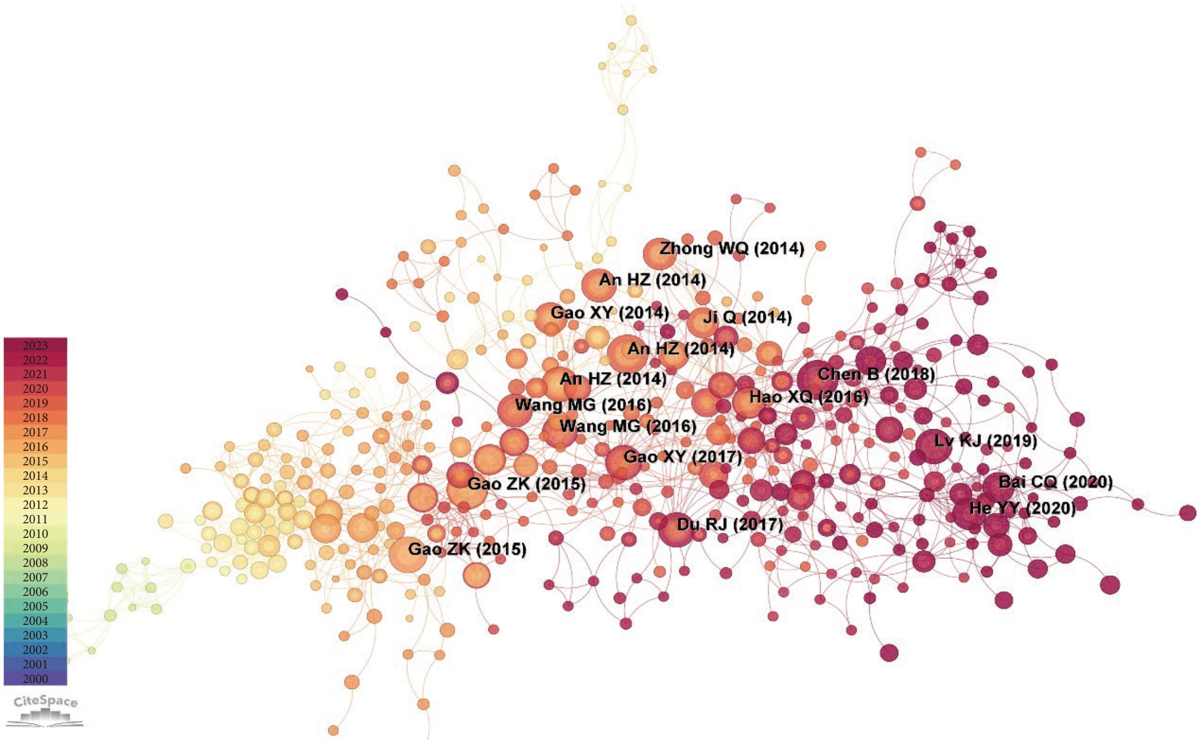

Fig. 6 Literature co-citation network. Notes: This figure was created by the authors using CiteSpace software. The size of each node represents the number of cited literatures, while the labels indicate the author information of the cited literature.

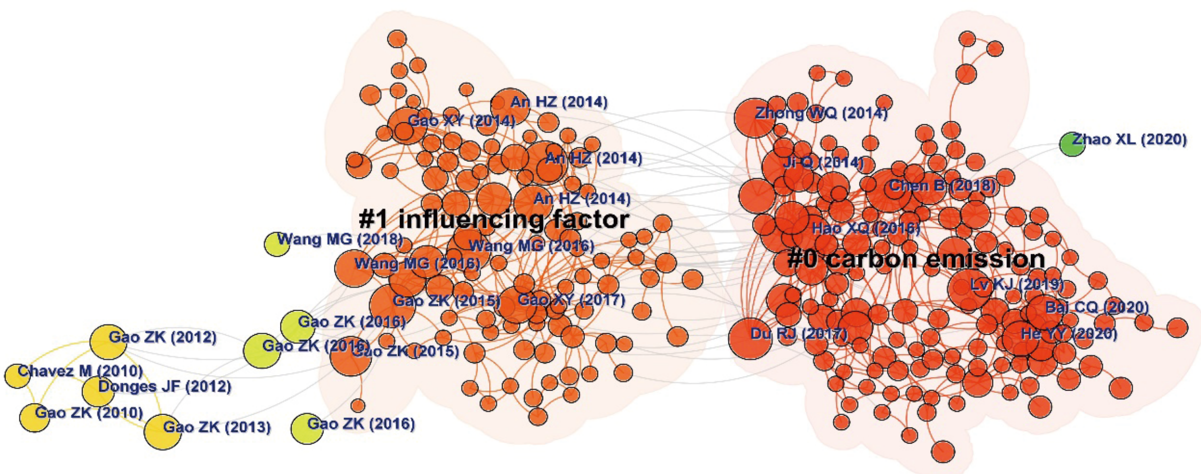

Fig. 7 Two largest clusters in the literature co-citation network.

Table 1 The top 5 key references in the two largest clusters.

#	Cluster 0	Cluster 1
1	Chen et al. (2018)[44]	An et al. (2014)[45]
2	Du et al. (2017)[46]	Gao et al. (2014)[47]
3	Lv et al. (2019)[48]	Wang et al. (2016)[49]
4	Zhong et al. (2014)[50]	Gao et al. (2015)[51]
5	Ji et al. (2013)[52]	Gao et al. (2017)[53]

represented as nodes, while edges depict the presence of renewable energy trade relations between countries. The weight of the edges is determined by the trade volume, making it a weighted directed network.

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4.2 Network indicators and result analysis

Determining the properties of nodes and weights through topology indicators is crucial as it can provide underlying economic interpretations. Commonly used network indicators in the existing research on E&C systems include density, degree centrality (DC), clustering coefficient (CC), betweenness centrality (BC), eigenvector centrality (EC), and community structure (see Table 2). These indicators are primarily classified into local and global categories.

Within our constructed renewable energy trade network, we calculate the aforementioned indicators, with a specific focus on the community structure. For community partitioning, we utilize modularity as a measure[63], as illustrated by Eq. (1).

$$Q = \frac{1}{2w} \sum_{ij} \left(w_{ij} - \frac{w_i w_j}{2w} \right) \mu(C_i, C_j) \tag{1}$$

where, w represents the sum of the weights of all edges in the trade network, w_i denotes the sum of the weights of all edges connecting to node i, and w_j represents the sum of the weights of all edges connecting to node j. If node i and node j belong to the same community, the value of $\mu(C_i, C_j)$ is 1; otherwise, it is 0. A higher modularity value closer to 1 indicates better partitioning results.

Based on Figures 8 and 9, it can be observed that solar energy has the highest trade volume but the lowest modularity value. This suggests that solar energy is highly integrated and active within the trade network. Conversely, hydro energy, despite having the lowest cumulative trade volume, exhibits distinctive characteristics in the trade network. This can be attributed to the fact that BRI countries possess significant solar energy potential, accounting for approximately 50% of the global solar energy potential. Consequently, these countries have favorable conditions for solar energy development and prioritize its growth, leading to high integration and activity within the trade network.

5 Limitations and outlook

Network modeling technology has been extensively utilized in the field of energy and carbon emissions. However, there are still several issues that require careful consideration. In the following discussion, we address some of these potential problems and propose possible solutions.

Table 2 Definition of commonly used network indicators[54–62].

Indicators	Abbreviation	Definition
Degree Centrality	DC	Node importance index based on the number of node neighbors.
Semi-local Centrality	SLC	
K-shell	K-shell	
Closeness Centrality	CC	Node importance index based on path.
Betweenness Centrality	BC	
Subgraph Centrality	SC	
Information Indices	II	
Eigenvector Centrality	EC	Node importance index based on eigenvector.
Average path length	L	Average distance between any two nodes.
Modularity	Q	Measuring the structural strength of network communities.
Community	Community	Grouping network nodes.
Normalized Mutual Information	NMI	Community-based network stability.
Density	Density	Characterizing the density of edges between nodes in a network.

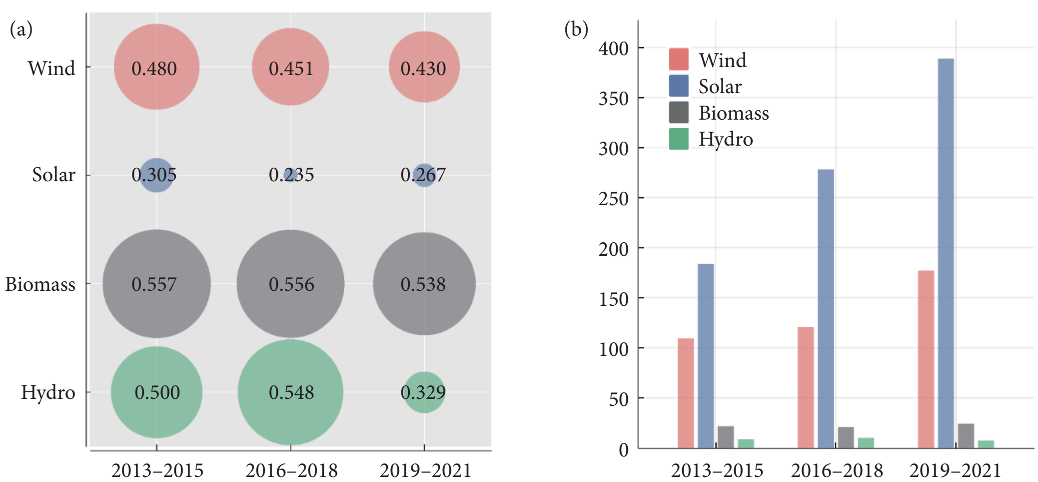

Fig. 8 Modularity results for different types of renewable energy. **(a)** Bubble chart for modularity value; **(b)** trade value in 100 million USD.

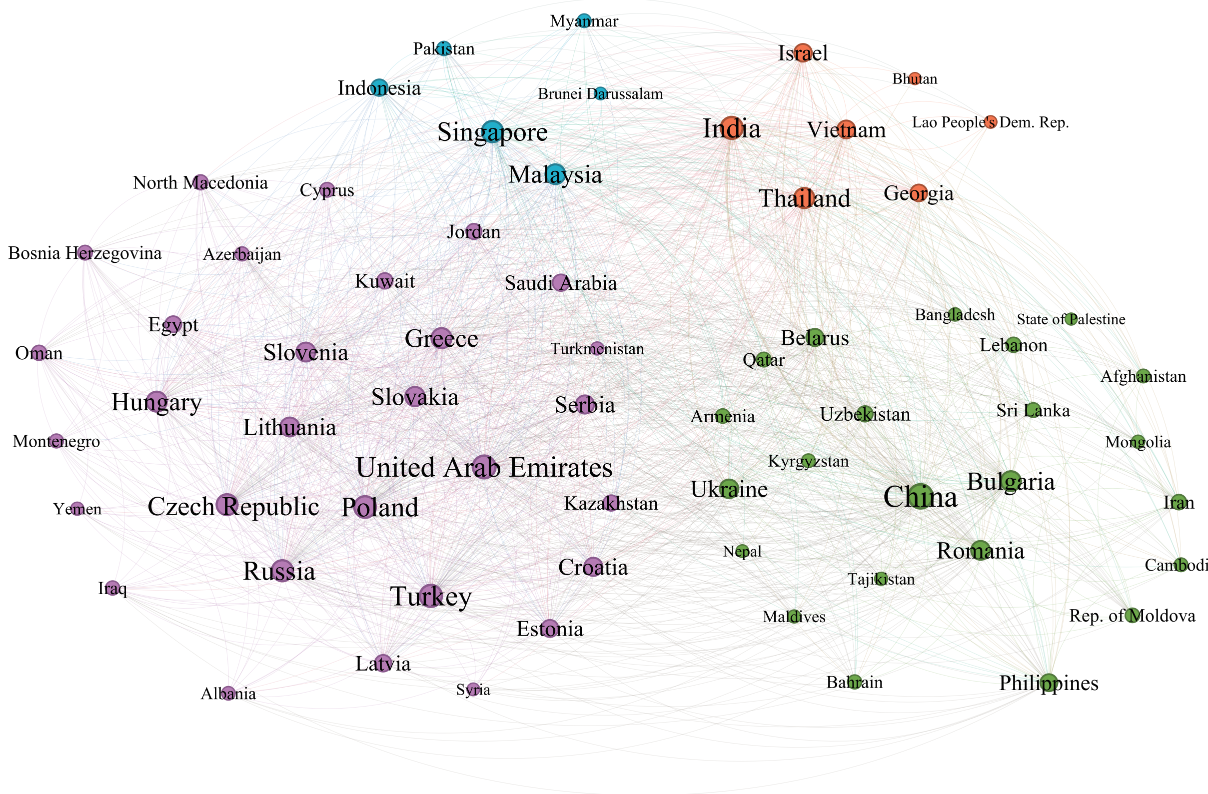

Fig. 9 Solar trade network and its community structure during 2019–2021.

5.1 Limitations

First, the measurement and interpretation of network topology are significantly limited. Existing empirical literature commonly employs network indices such as DC, strength, BC, CC, shortest path length (SPL), density, community structure, motif, and stability. However, relying solely on these metrics is insufficient to fully elucidate the network formation mechanisms. Moreover, some widely used indicators do not adequately reflect their economic implications.

Second, there is a reliance on local and global indicators. Metrics like node degree and clustering coefficient primarily focus on the local structure of the network, which may fall short in explaining the global characteristics and dynamics of the network. In some cases, these indicators oversimplify the actual network structure for the sake of ease in comprehension and calculation. For instance, symbolic networks only preserve positive and negative relationships between participating agents, neglecting more nuanced interactions.

Third, the description of multi-type relationships among participants is insufficient. In a practical scenario, the same participant may assume different roles despite the absence of physical links. For example, intermediate product suppliers serve as demand nodes for upstream producers while acting as supply nodes for downstream customers in supply-demand bipartite networks. In addition, due to the diverse range of products, supply and demand relationships are not singular. However, existing research lacks comprehensive descriptions in this regard.

Fourth, the complex and nonlinear relationships among participants are inadequately addressed. The dynamic and nonlinear characteristics of E&C systems pose challenges for complex network models in accurately capturing and predicting long-term trends and emergencies. What's more, network models are often tailored to specific situations or datasets, resulting in generalization and adaptability issues.

5.2 Future research directions

To overcome the above-mentioned limitations, future research in the field of complex network modeling for energy and carbon emissions should explore alternative or complementary network metrics that offer deeper insights into network formation mechanisms and economic implications. It is essential to incorporate multi-type relationships and consider the complexity and nonlinearity of E&C systems. Additionally, efforts should be made to develop more generalized and adaptable network models that can be applied across various contexts and datasets.

(1) Improving the interpretability of the network model. Enhancing the interpretability of network models requires employing a broader range of indicators that align with the specific research objectives. For example, by combining status theory and structural balance theory, one can assess the local or global stability of a symbolic network based on triangular relationships. This approach provides insights into the predictability of future system development[6].

(2) Research on multilayer network modeling. Future studies can extend beyond single-layer network models and explore the potential of multilayer network modeling[14, 64] (see Figure 10). In a multilayer network, also known as a network of networks (NoN), the same node can exist across multiple layers. Considering that E&C systems are interconnected with other complex networks, a multilayer network modeling approach is necessary to capture the intricate relationships and interactions within the broader context.

(3) Combining multiple methods to solve practical problems. To address practical challenges effectively, it is valuable to

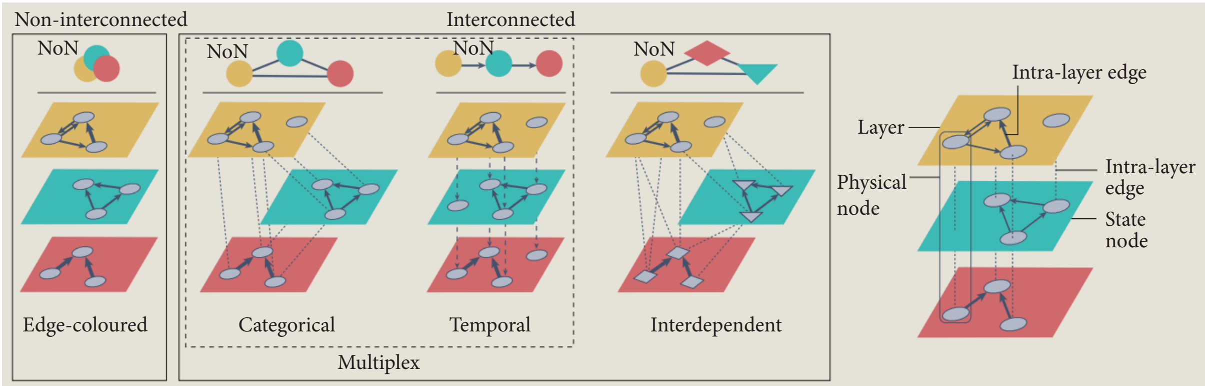

Fig. 10 A multi-layer network framework from Ref. [14].

integrate complex network analysis with traditional economic models, optimization theory, evolutionary game theory, machine learning algorithms, and other relevant methodologies. Such an interdisciplinary approach can facilitate optimal resource allocation, informed policy decision-making, and accurate price predictions[22]. By leveraging the strengths of different methods, researchers can gain a more comprehensive understanding of E&C systems and devise more robust solutions.

6 Conclusions

In this paper, a bibliometric analysis is conducted to review the application of complex network modeling in the field of energy and carbon emission systems. As complex network theory continues to mature, its practical application in understanding and explaining various complex systems, including energy and carbon emissions, is growing. Complex network modeling provides a robust analytical and research framework for analyzing and forecasting energy and carbon prices, evaluating energy carbon footprints, and optimizing supply chain connections. Nonetheless, despite the progress made, there are still several challenges to address in current research. One such challenge is the limited coupling of different types of energy networks, which is essential for constructing more reliable and efficient low-carbon energy transition systems. In addition, the exploration of network dynamics and time-varying characteristics in current research requires further enhancement to better adapt to the rapid changes in energy markets and policies. These challenges not only highlight the limitations of existing research but also show directions for future investigations. By addressing these challenges, researchers can expand the application of complex network modeling in the energy and carbon emissions domain, enabling the development of more comprehensive and effective strategies for achieving sustainable and low-carbon energy systems.

Acknowledgements

The authors are grateful for the comments from the anonymous reviewers of this paper. This work was partially supported by the National Natural Science Foundation of China (No.72243005), Major programs of the National Social Science Foundation of China (No. 22&ZD136), and Special Science for Carbon Peak and Carbon Neutralization of Jiangsu Province (No. BE2022612).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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