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Exploring Multi-Energy Convergence Through Knowledge Graphs and Patent Bibliometrics

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Abstract

Today, low-carbon, clean energies - renewables, hydrogen and nuclear - have begun to replace fossil fuels. This transition has been accompanied by an integration of new energy technologies in terms of shared use of energy, integration of multiple energy systems, and conversion between energy sources. Countries are actively building a low-carbon energy system with multi-energy integration to achieve the dual-carbon goal. This paper proposes to construct a multi-energy patent knowledge map and establish a domain knowledge organizing system based on fusing multiple technology classifications by integrating different patent technology classifying systems. Top-down and bottom-up approaches are adopted to build a conceptual model, and empirical research and validation are conducted in the field of low-carbon energy technology as an example to systematically analyze the development trend of low-carbon energy, convergence signals, and the potential of multi-energy convergence. The results are expected to provide insights into the development and practical application of multi-energy technologies and provide a basis for formulating relevant policies and research directions.

Introduction

Reducing carbon emissions to combat climate change is becoming a global consensus, and "dual carbon" (The goals for peak CO2 emissions and carbon neutrality) is an important strategic goal for most countries around the world in the next half century. Improving the energy supply structure is the linchpin and key to realizing the "dual carbon" path. In order to achieve this objective, it is imperative to gradually and steadily transition away from a coal-based energy structure towards a more robust and diverse energy portfolio. This transition requires the vigorous development of both renewable energy sources and safe and advanced nuclear energy. Additionally, it is essential to recognize the complementarity and large-scale potential of non-fossil energy sources, fostering a multifaceted approach to energy production and consumption. Presently, an array of low-carbon and clean energy sources is emerging. Such resources include photovoltaic, solar thermal, wind, nuclear, hydrogen, biomass, ocean energy, and geothermal energy. However, renewable energy is faced with significant challenges, including low energy density, high volatility, intermittent availability, and inherent randomness. Consequently, the implementation of renewable energy on a large scale necessitates a systematic integration of diverse energy sources within the overall energy system. For instance, wind and light resources can serve as the primary sources of power generation and energy supply, whereas nuclear power, hydropower, and analogous comprehensive and complementary non-fossil energy sources can be utilized as a "stable power source," with a modicum of thermal power functioning as an emergency power source or a regulating power source. The development of a new type of power system management and operational framework will be enabled by the integration of renewable energy power prediction technology, advanced power system stabilization and control technology, and innovative power system flexible interaction technology. Beyond electrochemical energy storage, mechanical energy storage, electromagnetic energy storage, and hydrogen energy, a broad range of energy storage methods is considered. Consequently, the focal point of establishing a multi-energy complementary integrated energy system is the mastery and realization of the core technology of multiple energy coupling and complementary (Li et al., 2022).

Technological convergence is the process of combining existing technologies into hybrid technologies (Curran, Bröring and Leker, 2010). This integration is not just about adding technology but innovating in unprecedented ways to create new markets. The convergence of technologies for different new energy sources encompasses the joint utilization of energy resources, the integration of multiple energy systems, and the interconversion of energy sources. For instance, the technology of using nuclear energy to produce hydrogen energy has emerged as a promising avenue for the future, offering a carbon-free approach to hydrogen production. Significantly, prominent developed nations such as the United States and the United Kingdom have unveiled comprehensive research and development plans with the objective of fostering the advancement and integration of these technologies, such as US's Nuclear Hydrogen R&D Plan (DOE, 2022) and the report Unlocking the UK's Nuclear Hydrogen Economy to Support Net Zero (National Nuclear Laboratory, 2021). Hydrogen applications aim to explore flexible and efficient multi-energy integration solutions while enhancing the performance of existing fuel cell systems (Yue et al., 2021). As hydrogen energy continues to be developed, its applications are expected to evolve from single solutions to composite systems. Examples include pathways from renewable power generation to hydrogen, methanol, and chemical feedstocks; and systems from electricity to hydrogen and power for use in exploring multi-energy integration based on hydrogen energy (Fu et al., 2020). In this paradigm, hydrogen emerges as a pivotal energy carrier, facilitating flexible complementarity among diverse energy sources and promoting decarbonization in multiple sectors, including power, transportation, chemicals, and steel, through conversion to electricity, heat, gas, or as raw materials (Li, He and Farjam, 2023).

Achieving carbon neutrality depends on the widespread adoption of renewable energy and new energy technologies. However, large-scale deployment of renewable energy is challenging. In particular, the synergistic and interactive use of different energy resources is crucial. To overcome these challenges, renewable energy sources such as wind and solar must be integrated with stable energy sources such as nuclear, hydro, and other non-fossil fuel sources. Thermal power can be used as an emergency backup. It is necessary to develop a new framework for managing and operating power systems. To do this, it is important to understand how different new energy sources can be integrated. Based on the multi-energy patent knowledge graph, we analyze the trends, convergence signals, potential and evolution paths of multi-energy integration using patentometrics. The research questions are as follows: What are the developments in the integration of different types of renewable energy sources? What is the potential for integrating multiple renewable energies? How does it work to integrate multiple renewables? What is the direction of low-carbon energy technology integration and technology evolution path?

This paper explores the domain knowledge discovery of technological convergence, proposing a method and process for doing so based on a convergence perspective. The investigation and analysis of existing patent technology classification systems and industrial classification systems worldwide is initiated to establish a foundation for the subsequent analysis. The design of an automatic mapping model of multiple classifications employs the integration of conceptual-level and data-level knowledge, aiming to merge disparate patent technology classification systems and construct a domain knowledge organization system. The proposed methodology integrates a top-down (knowledge conceptualization) and bottom-up (knowledge refinement) approach, facilitating the identification of domain knowledge. The top-down approach of knowledge concept refinement is integrated with the bottom-up approach of entity category summarization to construct the conceptual model of domain knowledge mapping. The constructed method is then applied to investigate technological innovation opportunities and evolution paths. An experimental study is conducted in the field of low-carbon energy technology to verify the feasibility and validity of the constructed methodology and process.

This paper focuses on two main aspects of technological integration and development trends in major low-carbon energy technologies. Firstly, it analyses the technological integration trend of various low-carbon energy technologies based on a multi-energy patent knowledge map. Secondly, it clarifies the main technological direction and evolutionary path of multi-energy integration. The primary objective of this study is to provide a comprehensive basis for the formulation of relevant policies and research directives.

Literature Review

Renewable Energy and Patent Classification

Major national intellectual property offices and organizations in the world have established patent classification systems in the field of renewable energy, covering the concept of "multiple energy sources" and the classification system (**Error! Reference source not found.**), including seven types of renewable energy sources, such as solar, wind, nuclear, hydrogen, biomass, ocean, geothermal and other renewable energy sources. The patent classification system related to green transition technology is a low and zero carbon energy-related technology classification or patent search formula formed through the discussion of experts in the field, which facilitates the wider use of it to conduct patent information analysis. In this context, WIPO has created a patent classification index for climate change mitigation technologies that are consistent with the existing International Patent Classification (IPC) system. China and Japan, which are relatively late in adopting it, are formulating it from an energy supply and utilization from industry and electric power generation perspective. The newly established Y02E (low-carbon energy generation, transmission and distribution technologies) in the Joint Patent Classification System for European-American cooperation. The diversification of classification systems has two notable effects. On the one hand, it provides richer paths for accessing information. On the other hand, it significantly increases the uncertainty factor. In cases where multiple knowledge sources correspond to the same technical feature, each source may adopt a different technical classification and attribute framework. This often leads to fragmentation of knowledge organization. As a result, issues such as knowledge redundancy, semantic ambiguity, and inconsistent quality may arise. These problems exacerbate the uncertainty in the knowledge acquisition process. They also challenge the reliability and confidence level of the knowledge. In this context, the effective integration and fusion of multi-source knowledge have become essential strategies for enhancing the accuracy of knowledge discovery.

The central objective of this section of the study is to employ conceptual-level knowledge fusion techniques, with the aim of integrating the same knowledge source—which utilizes different classification and attribute systems—into a unified global framework. This process focuses on solving key issues such as conflict detection, entity disambiguation, entity alignment, and collaborative reasoning that arise when different classification systems point to the same knowledge content. It also lays a solid foundation for the seamless integration of multiple technology classification systems.

The paper systematically summarizes and reorganizes seven categories of low-carbon energy, including major technology categories, industry divisions, and domain-specific classifications, which are then further linked to the corresponding entries in the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC) systems. This process of summarization and reorganization serves to enhance the coherence and consistency of knowledge representation. Moreover, it provides a clearer and more comprehensive perspective for the subsequent analysis of technology integration and innovation.

Table 1. Patent Classification of Multiple Energy Sources.

Organization	*Patent Classification*	*Different Definition*
CNIPA (CNIPA, 2023)	Patent Classification System for Green and Low Carbon Technologies	Fossil Energy Carbon Reduction; Energy Conservation and Recycling; Clean Energy; Energy Storage; CCUS
WIPO (WIPO, 2010)	WIPO IPC Green Inventory	Nuclear power generation, alternative energy (biofuels, fuel cells, hydrogen, wind, solar, geothermal, waste heat, etc.)
USPTO EPO (USPTO; EPO, 2010)	CPC classification	Y02E (low-carbon technologies related to energy production, transmission and distribution) Y02E10/1 (geothermal), Y02E10/2 (hydro), Y02E10/3 (ocean), Y02E10/4 (solar thermal), Y02E10/5 (photovoltaic), Y02E10/7 (wind), Y02E50/1 (biofuels), Y02E50/3 (waste fuels), Y02E30/1 (spent biofuels), Y02E30/1 (nuclear fusion), Y02E30/3 and Y02E30/4 (nuclear fission)
USPTO (USPTO, 2009)	EST Concordance	Alternative energy: biomass, fuel cells, geothermal energy, hydroelectric energy, solar energy, wind energy
JPO (JPO, 2022)	Green Transformation Technologies Inventory	Energy Supply (gxA): Photovoltaic Power Generation, Solar Thermal Power Generation, Wind Power Generation, Geothermal Power Generation, Hydropower, Ocean Energy Power Generation, Biomass, Nuclear Power Generation, Fuel Cells, Hydrogen Technology, Ammonia Technology

Low-carbon technologies and Patent Analysis

Patent bibliometrics is an important method for studying the innovative output of low-carbon technologies. Analyzing low-carbon energy patent data can provide insights into the development trends and trajectories of low-carbon technologies. Oltra and Saint Jean (2009) argues that patents are a useful means of measuring green energy technologies. They can analyze invention activities in specific technological fields, the international dissemination of technology, the research and technological capabilities of enterprises, and the sources of knowledge of innovative institutions, as well as technological spillovers. Albino et al. (2014) analyzed the development and impact of low-carbon energy technologies, examining nuclear power production, alternative energy production, and energy conservation patents in The IPC Green Inventory, and found that the United States is the main source of innovative low-carbon energy technologies, while Japan leads in solar energy and low-energy lighting. Although China, Russia, and other countries are increasingly using low-carbon energy technologies, the level of technological innovation in this area remains low. Leu, Wu and Lin (2012) analyzed the status of technology development in the field of biofuel and biohydrogen energy on the basis of patentometrics, and found that the U.S. is leading the development of biofuel-related energy, and the high number of cited patents suggests that biofuel production technology must give priority to low energy demand. Liu et al. (2011) classified patents related to photovoltaic technology based on keyword co-occurrence and analyzed the growth trajectory of five groups of photovoltaic technologies. Chen, Chen and Lee, (2011) conducted a bibliometric and patent analysis to study the technological evolution and patent strategy of hydrogen energy and fuel cells. Subtil Lacerda (2019) examines the influence of scientific knowledge on the evolution of wind turbine technology trajectories through bibliometric analysis and finds a strong correlation between the development of scientific knowledge and the technological trajectories of wind turbines. Similarly, Hötte, Pichler and Lafond (2021) analyzed the relationship between low-carbon energy technologies and scientific knowledge. By analyzing a corpus of patents covering six renewable energy technologies from 1970 to 2019, Jiang et al.(2022) sheds light on the life cycle of these technologies, the technological landscape, the potential markets, and the competitive landscape in key countries/regions involved. The current study is mainly a descriptive analysis of LCE, which is limited by data availability and data processing capabilities. Second, the static patent classification system on which LCE is based is not perfect. It does not analyze trends in multi-energy convergence. The boundaries between fields are not clear and may evolve with dynamic cross-field convergence.

Second, technology convergence research based on patent information has become the main method and hot direction of technology convergence research. In addition, there are related studies that use data from papers, standards, and Wikipedia. For measuring technology convergence, Herfindahl Index, patent cross-impact analysis, social network analysis, and time window analysis are applied(Jeon and Suh, 2019; Lee, Kogler and Lee, 2019). In predicting technology convergence trends, methods such as link prediction based on technology convergence networks(Park and Yoon, 2018), neural network method based on technology convergence matrix (Kim and Lee, 2017), and time series prediction method based on time series of technology convergence relationships(Lee, Park and Kang, 2018) have been applied. Xue and Shao (2024) identifies technological evolution paths in the field of hydrogen energy using patent text mining. The analysis shows a good convergence in the evolution of hydrogen energy technologies, focusing mainly on hydrogen storage materials, hydrogen fuel cell vehicles, and green hydrogen production. Existing research shows that technology convergence positively affects technology value and innovation activity. Most empirical studies, however, are highly generalizable across domains. Few studies analyze the dynamics of technology convergence for multiple domains and across domains. At present, there are fewer studies on technology fusion analysis for patent data that target multi-domain and domain-wide technology fusion dynamics. This study attempts to fill this research gap by constructing a multi-energy fusion patent knowledge map.

The Knowledge Graph (KG) and Knowledge Discovery

The Knowledge Graph is a structured Semantic Web knowledge base that describes concepts and how they relate to each other in a visual way by mapping abstract data and knowledge to graphical elements(Dessì *et al.*, 2021). It complements human-computer interaction by helping users effectively perceive and analyze data and knowledge while exploring connections to extend existing knowledge(Xiao, Li and Thürer, 2023). It can mine and analyze knowledge and its interrelationships and are important tools for paying attention to the frontiers of science and technology and knowledge management. The existing studies mainly focus on the concept, development history, structure, application and so on aspects of knowledge maps(Nguyen and Chowdhury, 2013; Balaid *et al.*, 2016). Based on co-word analysis, social network analysis and strategy analysis, Pino- Díaz *et al.*, (2012)proposed the method of constructing techno-scientific network strategic knowledge map, which can visualize strategic knowledge, keywords, subnetwork proximity and other contents. Su and Lee, (2010)proposed a three-dimensional network and a two-dimensional map based on the co-occurrence of keywords, which can describe the forward-looking knowledge structure of the latest technology in a quantitative and visual way. The concept of a knowledge graph remains undefined, and research in this area is still in its early stages. Most researchers are now building knowledge graphs as navigational aids (network analysis, visualization, or text mining, etc.), which play an important role in organizing knowledge acquisition, connecting experts, discovering knowledge, and facilitating mobility (Lee and Fink, 2013). Key challenges include domain knowledge organization, dynamic/tacit knowledge representation/extraction, and cross-domain knowledge mapping (Suresh and Egbu, 2004). Zhou *et al.* (2024) maps knowledge on hydrogen fuel cell technology on the basis of bibliometrics and IPC co-classification analysis.

Karlapalem (2021) believes that Knowledge Discovery in Database is an important process for identifying valid, novel, potentially useful and ultimately understandable patterns in data, which refers to the extraction of implicit, unknown and potentially useful information from data (Fayyad, 2001), and the term refers to research results, technologies and tools that extract useful information from a large amount of data(Agrawal and Shafer, 1996). The extracted information includes concepts, relationships between concepts, classifications, decision rules and other information(Vickery, 1997). Knowledge discovery emphasizes that knowledge is the product of data-driven discovery process, a common point of different research fields, focusing on data analysis and knowledge extraction from different perspectives, such as database, statistics, mathematics, logic or artificial intelligence (Mariscal, Marbán and Fernández, 2010). Due to the complexity of knowledge and the Fusibility of technologies, it is very important to adopt appropriate methods and perspectives for knowledge discovery and analysis. In recent years, various knowledge discovery methods have been rapidly developed and widely applied in various industries, such as cancer diagnosis, biological classification of river water quality, population analysis, quality control, disaster risk assessment, global climate change modeling, time series pattern analysis, clinical medicine (Sebastian and Then, 2011; Anguera et al., 2016), topology optimization (Yamasaki, Yaji and Fujita, 2019), etc. Roscher et al.(2020) analyzed the application of explainable machine learning in natural science, holding that its main goal is to obtain new scientific insights and discoveries from observation or simulation data, and that the prerequisite for obtaining scientific results is domain knowledge, and defined the concepts of transparency, interpretability, and explainability.

Existing knowledge discovery techniques, research methods, perspectives, and outcomes are increasingly exhibiting a trend toward diversification. To accurately describe and reveal the knowledge structure and evolution characteristics, and to avoid discovering local and one-sided knowledge, it is necessary to integrate heterogeneous data from multiple sources. Furthermore, the knowledge organization system must be improved to maximize the discovery of the domain knowledge structure and the dynamic evolution characteristics from the perspective of data and technology convergence.

Methodology

The process consists of three main steps. First, we develop a system to organize domain knowledge using a technology classification framework derived from various sources. Next, we construct a knowledge graph. Finally, we leverage a multi-energy knowledge graph to conduct empirical research on technology convergence.

Domain knowledge under a multi-source technology classification system

This study employs conceptual-level knowledge convergence, a process aimed at integrating knowledge sources from various classification and attribute systems into a unified global framework. The theoretical underpinnings of knowledge classification and fusion of multi-feature representations (see Fig. 1) serve as the foundation. Initially, the knowledge system of the domain is extracted. Then, through the direct merging of the extracted data, the representation of "concept, attribute and attribute value" is formed (e.g., wind energy, IPC/CPC).

Subsequently, the entity references are categorized based on the established classification and fusion rules. The specific principles that have been adopted are as follows:

First, classification principles: (1) concept mutual exclusion constraint, i.e., the more intersected, the more compatible the concepts; (2) hierarchical concept constraint, i.e., an entity does not belong to a certain concept, and it does not belong to any sub-concepts.

Second, fusion principles: (1) concept fusion, which refers to synonyms or similar concepts; (2) attribute alignment, i.e., the degree of overlap of entity-attribute values corresponding to attributes; and (3) attribute value alignment, i.e., deletion of duplicates and elimination of erroneous knowledge.

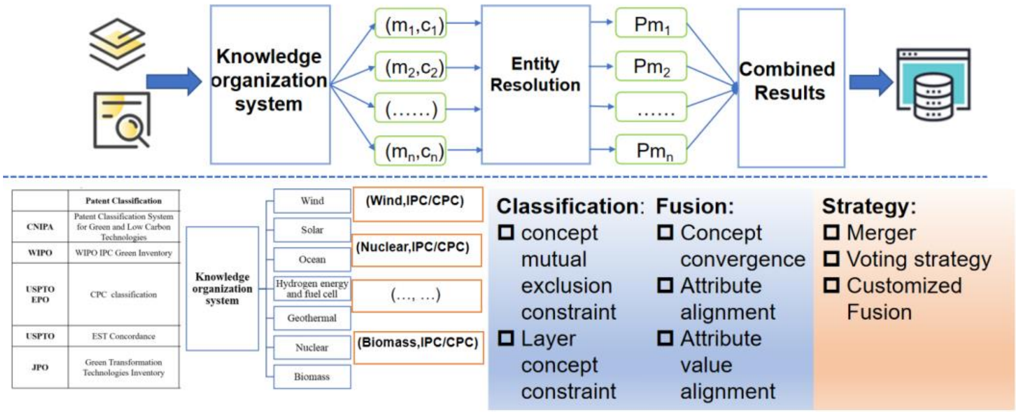

Figure 1. Theoretical Foundations of Knowledge Classification and Fusion Based on Multi-Feature Representation.

The theoretical foundation outline above serves as the basis for the development of the automatic mapping model of classes for multiple classifications (Fig.2). This model specifically incorporates two levels of patent classification feature fusion methods.

(1) Concept layer convergence

The first layer involves the convergence of text-based and structure-based approaches. The text-based method entails matching of the ontologies through the textual description information, the extraction of the descriptions from two ontologies, and the similarity between them. The structure-based method utilizes structural information between the ontology concepts when the textual information is inadequate for determining the matching relationship between two ontologies.

Initially, the text in "concept, attribute and attribute value" is extracted, including the text of technical categories, explanations, and IPC classification descriptions. Subsequently, the extracted text information is used to map into various vectors that can be corresponded to, in the form of, e.g. $\overline{\mathrm{wind}} = \left(w_{i,1}, w_{i,2}, w_{i,3}, \cdots, w_{i,n}\right)$, which is the set of vectors. Thirdly, the semantic similarity between the vectors is calculated by using the cosine similarity, the Euclidean distance, and other metrics. The calculation of semantic similarity between the vectors is performed using cosine similarity, Euclidean distance, and other metrics.

(2) Data layer convergence

An instance-based approach is adopted in this context. The instances of ontology concepts are utilized as the basis for similarity measurement when calculating ontology similarity. The number of identical instances of two ontologies is compared to calculate the similarity between ontologies. The greater the similarity, the closely the two ontologies align. This method is highly reliable.

The specific operational procedure is outlined as follows: Initially, the IPC classification number and attribute value corresponding to the ontology are extracted. Subsequently, under specific conditions, the probability model is employed to ascertain the matching relationship between the entities in question, i.e., the IPC classification number and other entities (single patents) with an IPC relationship.

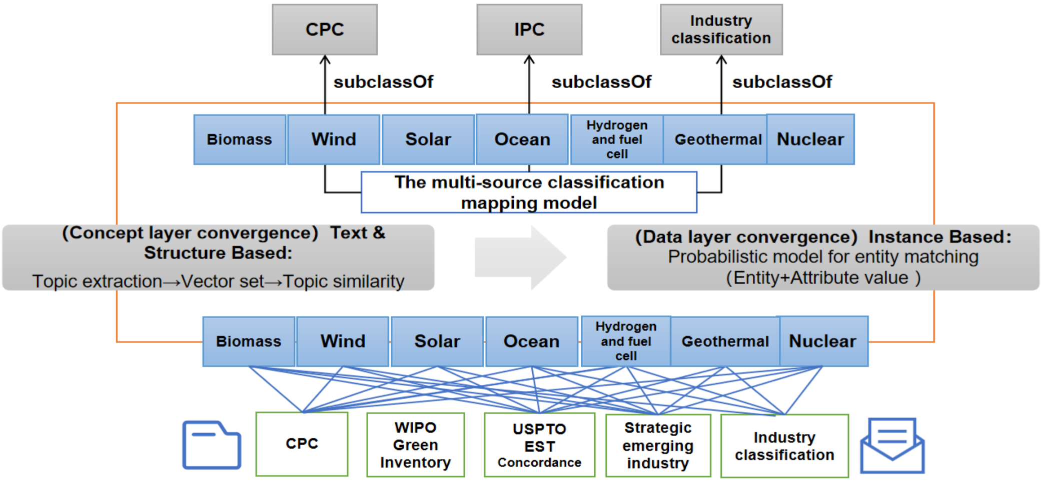

Figure 2. The multi-energy classification mapping model.

Multi-energy Knowledge Graph

The conceptual model of Multi-energy Knowledge Graph is constructed by combining top-down and bottom-up approaches (Fig.3). Firstly, top-down approach utilizes the knowledge organization system to gradually refine the concepts from the top level down to form a tree-structured mapping model. Secondly, bottom-up approach uses the patent data, which has been summarized by the related entity categories, to form a broad category scope layer from multiple fields of patents upward, thereby forming a general patent knowledge graph. The final step involves the combination of the two approaches to form a generic patent knowledge mapping by means of attribute extraction, attribute alignment, relationship construction, concept hierarchy construction and entity classification, etc., to obtain data and realize the construction of domain-specific knowledge graph.

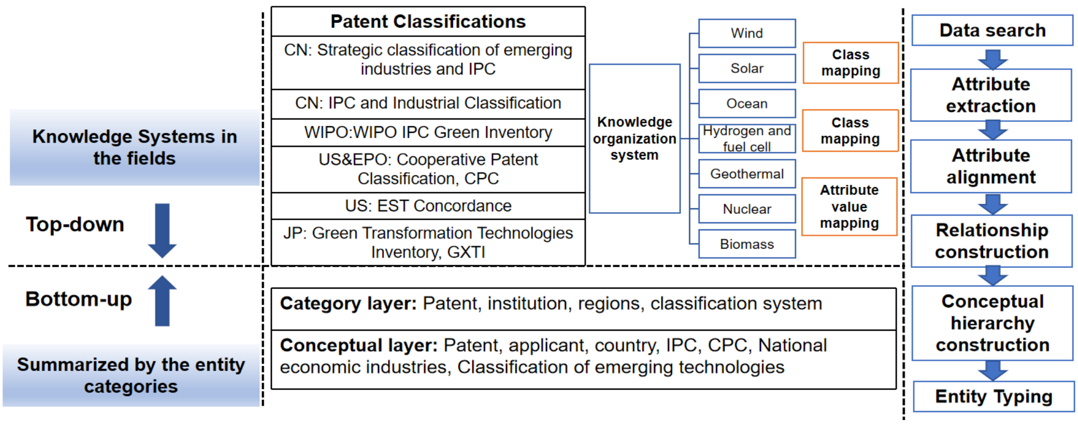

Figure 3. Method for constructing multi-energy knowledge graph.

Data search strategy

The data source of this study is the emission peak and carbon neutrality patent information platform (www.cpnp.ac.cn) built by the Chinese Academy of Sciences based on the web, which is a one-stop and patent big data information service platform, and contains a large amount of emission peak and carbon neutrality patent information worldwide. This platform has strong professional relevance and supports the comprehensive collection of patent data relevant to various energy sources, which is highly consistent with the research topic. In this paper, we searched for priority patents related to low-carbon zero-carbon energy, energy storage and multi-energy integration technologies to ensure the timeliness and novelty of the data. The search results involved a total of 7 technology branches, and obtained more than 1.5 million pieces of relevant patent data (Table 2). The search was conducted in April 2022.

Table 1. Patent search strategy and data proportion.

Fields	*Secondary Fields*	*The Number of Patents*	*Proportion (%)*
Low-carbon and zero-carbon energy (1,041,553)	Nuclear power and non-electric use of nuclear energy	131,903	12.6%
	Renewable energy (Solar, wind energy, biomass energy, geothermal, ocean energy)	716,720	68.5%
	Hydrogen energy and fuel cell	198,266	18.9%
Energy storage and multi-energy integration	Heat/cold storage	55,065	10.2%
	Physical power storage	44,051	8.2%
	Chemical power storage	416,783	77.5%
	New power systems based on renewable energy	21,605	4.0%

Technical comparison indicators

We combines the characteristics of different technical fields and introduces the following two technical comparison indicators:

(1) Technology comparative advantage

Low-carbon clean energy technologies can be categorized into the following: renewable energy, hydrogen and fuel cells, nuclear power, and non-electric utilization of nuclear power. Energy storage and multi-energy integration technologies can be categorized into the following: thermal energy storage, new power systems based on renewable energy, chemical power storage, and physical power storage. The patent technology dominance of country j in the ith technology field (second level) can be calculated by formula (1-1) using the internationally recognized multi-disciplinary measurement index "technology comparative advantage" (RTA).

$$RTA = \frac{P_{ij}/\sum_i P_{ij}}{\sum_j P_{ij}/\sum_i P_{ij}} \tag{1-1}$$

In equation, P_{ij} denotes the number of patents of the jth country in the ith technology field.

(2) Technological relevance

The integration of wind energy with other energy technologies has become increasingly prominent. The coefficient of technological relevance is employed to assess the technological relevance of the seven energy sources. Compared with indicators such as Jaccard Index or Salton Cosine, which can only capture the differences between technologies, the correlation coefficient can capture the distance between two technologies and is more conducive to evaluating the closeness of the relationship between technologies. A larger value indicates a closer relationship between the two technologies. The calculation method is delineated in equation (1-2):

$$S_{ij} = \frac{\sum_{n=1}^{k} C_{in} C_{jn}}{\sqrt{\sum_{n=1}^{k} C_{in^2}}\sqrt{\sum_{n=1}^{k} C_{jn^2}}} \tag{1-2}$$

In equation (1-2), S_{ij} denotes the correlation coefficient between technologies i and j. If S_{ij} is equivalent to 1 on the diagonal of the correlation matrix, it signifies that the co-occurrence distribution of technologies i and j in patents is entirely consistent, indicating a complete integration of each technology with itself. Conversely, if S_{ij} is 0, it indicates that the distribution of patents for technologies i and j is entirely disjoint. K represents the number of core technologies, which is to say the width of the integration of the technologies is represented by Cjn, which denotes the number of instances in which technologies j and n are present together in a single patent.

Empirical Study of Convergence application of Multi-energy Knowledge Graph

The domain of low and zero-carbon energy technologies has been selected as a subject of in-depth experimental research. This decision stems from two primary considerations. Firstly, green and low-carbon technologies are garnering increased global attention, prompting prominent scientific and technological powerhouses, as well as regional organizations, to dedicate considerable resources to the promotion of research and development in the field of green technologies. Notably, the development of patent-technology classification systems, a crucial component in the patent information search strategy, is experiencing robust growth. This system is instrumental in facilitating a comprehensive and systematic understanding of the patent landscape, thereby providing a solid knowledge framework and conceptual foundation for the execution of this research method.

Secondly, international science and technology and industrial communities have urgent strategic needs for low-carbon energy and multi-energy fusion technologies. An in-depth investigation of this technological innovation trend in the field can track the development of innovation and application among low-carbon energy supply technologies. It can also quickly capture the characteristics of technology convergence and its path evolution trends. This is imperative for the development of a low-carbon energy system integrating various energy sources and for providing a scientific foundation for related innovation decisions.

Knowledge Organization for Multi-energy Classification

In view of the major strategy of low-carbon energy and the demand for multi-energy integration, the concept of "multi-energy" and its classification system have been investigated. A comparative analysis demonstrates that the World Intellectual Property Organization (WIPO) and the United States Patent and Trademark Office (USPTO) have pioneered the Green Patent Technology Classification System, with the classification primarily devised from an alternative energy perspective. In contrast, the Joint Patent Classification System of Europe and the United States has recently augmented its classification with the addition of category Y02E (low-carbon technologies associated with energy generation, transmission, and distribution). Meanwhile, China and Japan have demonstrated a bias towards the perspectives of energy supply and utilization in the new energy industry and the electric power production industry (Guo R, et al., 2020).

The present study, which is based on the patent technology classification systems mentioned above, draws upon the technical characteristics of the respective fields. It identifies and explores the knowledge concept space of seven types of low-carbon clean energy, such as solar, wind, nuclear, hydrogen, biomass, ocean, and geothermal energy, and conducts research on the construction of a low-carbon energy knowledge organization system within the multifaceted technology classification system.

For each of the seven types of energy, the main technology classifications, industries, and industry domains are thoroughly examined, with the corresponding IPC and CPC classification numbers documented. The attribute characteristics of these energies, as classified in different systems, are unified to facilitate the realization of conceptual and data level fusion, resulting in a comprehensive global system.

The knowledge organization process for wind energy is exemplified by its integration of a technology classification system that delineates wind energy and its associated technology branches. Initially, the technology classification system of wind energy is merged, providing a comprehensive overview of wind energy and its associated technology branches. From a textual feature perspective, the first level encompasses all wind energy (F03D), adhering to the principle of majority same, ensuring a precise alignment between the two-ontology information. Subsequently, from a structural feature perspective, the subordinate technology branches, such as F03D1 with F03D as the parent node have a higher probability of being matched; third, H02J3/38 has a matching relationship with multiple entities belonging to the same class of H02J (wind power generation).

Knowledge Graph in the field of low-carbon and zero-carbon

Based on a multi-energy knowledge organization system, a multi-energy knowledge graph is built by collecting data, extracting attributes, aligning, building relationships, building concept hierarchies, and classifying entities. As shown in Fig.4 and Fig.5, entity, relationship and attribute knowledge are extracted from patent fields, and structured knowledge within the knowledge graph is linked and enhanced using knowledge graph construction techniques like entity linking and entity complementation. Finally, the knowledge graph in the field of low-carbon energy technologies will be formed and stored in the Neo4j.

Entity type	Entity Examples
Patent	US20130259187A1
	Rockfuel Innovations Limited
	Ipswich Suffolk GB
	C3583
	C10K
	6.2

Entities	Relations
1698	195,475

RelationTypes	Relation Examples
Coexist	(US9748006B2, COEXIST, US9691508B2)
IPCis	(FR920290A, C2619, 1, GMJJIS)
	(FR1180356A, 3.2.1, XXCYIS)
	(FR920290A, C01B,1, IPCIS)
Belongs	(FR920290A, ICI LTD, 1, BELONGS)
Whereis	(JP2905705B2, Japan, 1, WHEREIS)
	(SHINKO PANTETSUKU KK, Japan, 1, COUNTRYIS)

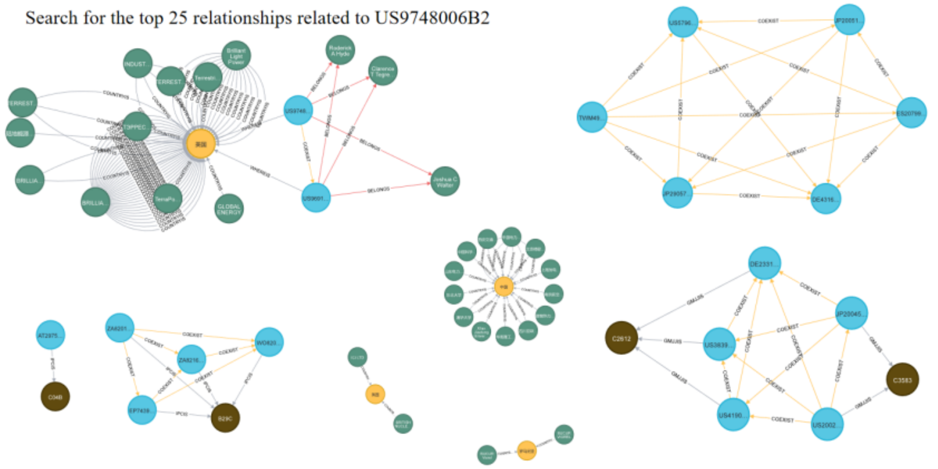

Figure 4. Example of Knowledge Graph Entity Relationships in the Low-Zero Carbon Domain.

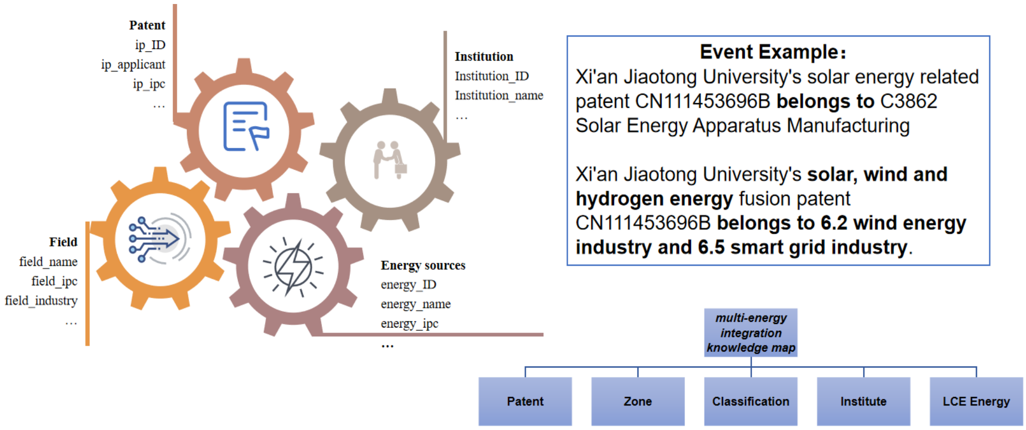

Figure 5. Event Example for Multi-energy Knowledge Graph.

Evolutionary Analysis of Technology Convergence Paths in the Low Carbon Energy Field

This study employs a knowledge discovery method based on the integration of multiple low-carbon and clean energy technology classifications; a methodology previously outlined in prior research. This paper utilizes patent analysis and application to examine the current state of knowledge reserves in the field, with the aim of identifying opportunities for technological innovation and evolutionary paths in the field of low-carbon and clean energy.

Seven low-carbon clean energy technology convergence trends

(1) The first signal of convergence is an inevitable product of the development of the multi-energy technology——from wind and ocean power to nuclear, hydrogen and solar PV. As it shown in Fig.6, in the 19th and early 20th centuries, hydroelectricity and wind power accounted for the largest share at over 60%. After the World War II there was a shift to nuclear fission, with nuclear power accounting for up to 46% of the total, and after 1975 a shift to solar PV and wind power, which together accounted for almost 45% of the total in the same period. The analysis revealed a general upward trend in renewable energy-related patents, with a marked increase occurring subsequent to 1980 and accelerated growth following 2005. The study also noted considerable variability in the development of distinct energy technologies, with wind energy patents dating back to 1907 and biomass-related patents emerging only after 1970. The patents demonstrating the most significant growth and proliferation are those associated with wind and solar energy. In contrast, patents related to ocean water energy, hydrogen energy, biomass energy, and nuclear energy have experienced a notable surge in innovation between 2011 and 2015, followed by a subsequent decline in recent years.

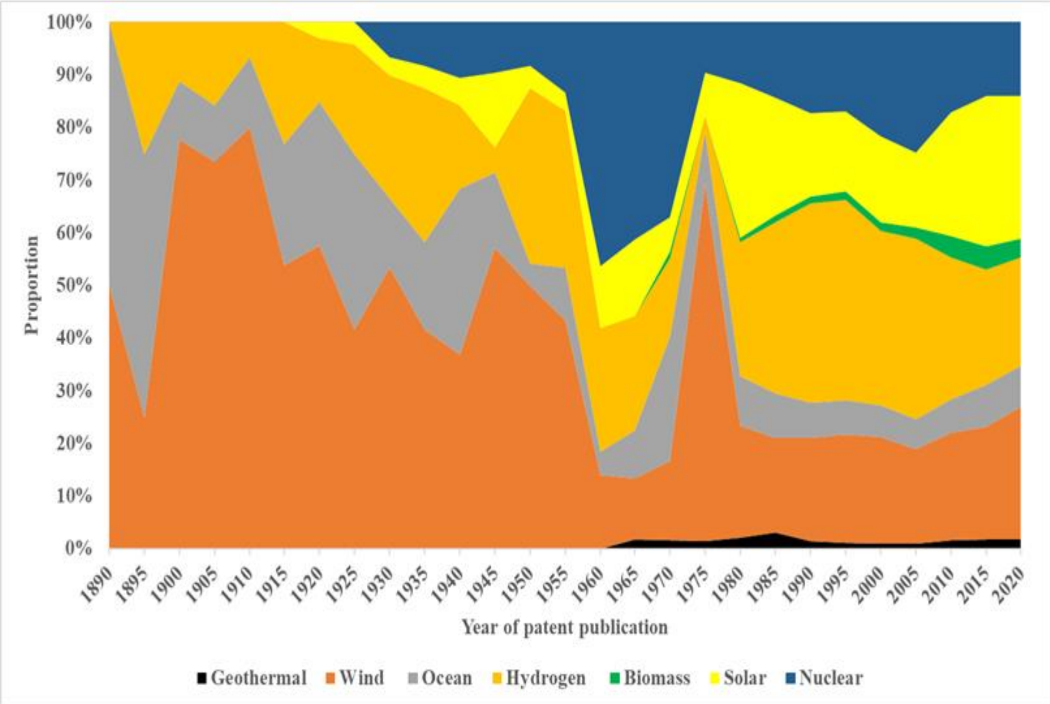

Figure 6. Trends in Multiple Energy Patent Applications (1890-2020).

(2) A second signal of technology convergence is the increasing share of cited papers in the total number of patents (Fig.7). The first patent literature on renewable energy technologies emerged in the early 20th century, yet the majority of citations to relevant scientific papers within this patent literature materialized subsequent to the 1970s. This observation suggests a growing reliance on scientific research with the progression of low-carbon clean energy technologies, particularly within the domain of biomass energy. Along with the steady rise in the number of patents filed for these seven low-carbon clean energy technologies, there has been an analogous increase in the proportion of relevant patents citing relevant papers. In recent years, biomass energy has become the most science-dependent energy source due to its close links to biochemical research, with 33-57% of cited papers. Nuclear, hydrogen and photovoltaics are also more science-dependent than other technologies (especially hydro and wind). Science-intensive technologies tend to be more dependent on basic science than on applied technologies across a wide range of energy sectors. A close examination of the seven low-carbon clean energy technologies reveals that the development of biomass energy technology is most dependent on basic scientific research. This is due to the fact that the technology is closely related to biochemical research. Consequently, this feature is the most distinctive. In contrast, the remaining energy technologies, particularly hydropower and wind energy, exhibit a stronger correlation with applied research.

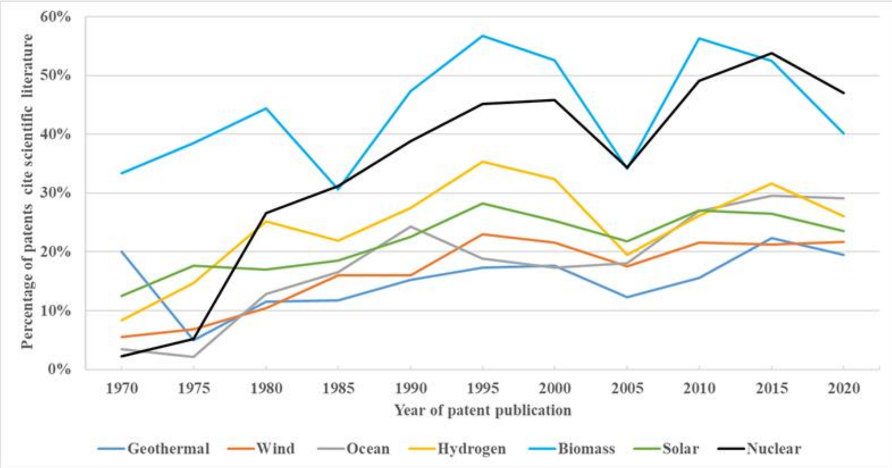

Figure 7. Trends in the percentage of patents citing paper (1970-2020).

(3) A third signal of technological convergence is that the convergence of multiple energy sources is based on the same or similar scientific principles. Statistics on the number and type of IPC top 4 for the full set of patents for various LCE show that 221 sub-categories are involved in the field, of which solar PV has the highest number of IPC categories involved with 81.The basis for the multi-energy integration of the various energy is the physics of nuclear energy integration based on plasma (G), ocean and geothermal energy based on mechanical engineering (F), biofuels and hydrogen fuel cells based on chemistry (C), and solar PV and wind energy based on photoelectric effects (F&H). Tables 3 and 4 provide mutual corroboration of the basis for the convergence of multiple energy technologies in terms of quantity and type, respectively.

Table 2. Number of IPC Top 4-Digit Classification Based on Seven Energy Sources.

Energies	G	B	C	E	F	H
Nuclear	**215**	98	269	2	84	62
Wind	584	602	176	466	7687	4418
Solar	632	557	706	420	**4827**	**4607**
Biomass	3	297	**1799**	2	183	164
Ocean	19	301	83	124	**4329**	249
Geothermal	9	16	20	81	**847**	66
Hydrogen	178	598	2640	31	902	737

Table 3. Types of IPC Top 4-Digit Classification Based on Seven Energy Sources.

Energies	G	B	C	E	F	H	Y02
Nuclear	**12**	2	1	2	1	0	3
Wind	0	6	1	2	**15**	8	6
Solar	1	1	2	2	**25**	**33**	17
Biomass	1	2	24	1	5	1	0
Ocean	0	2	1	4	9	1	2
Geothermal	0	0	0	2	12	2	1
Hydrogen	0	1	0	2	1	1	4

(4) The RTA was used to compare and analyze the patent-protected technologies of major global science and technology powers (China, Japan, the United States, Germany, and South Korea). These countries were selected based on their status in two key fields: low-carbon and zero-carbon energy, as well as the storage and convergence of multiple energy sources.
(5) The calculation results reveal that China possesses a substantial relative advantage in the domain of low-carbon clean energy (Fig.8), with its renewable energy patented technology. Japan's strengths lie primarily in nuclear power and non-electric utilization technology, while the United States leads in nuclear energy, hydrogen energy, and fuel cells. In the domain of energy storage and multi-energy integration (Fig.9), China has a substantial advantage in heat and cold storage, new power systems based on renewable energy, and chemical storage. In contrast, Japan and the United States prioritize chemical storage, while Germany focuses on physical storage.
(6) The world's major technological powers each possess a distinct set of advantages in terms of energy sources. The RTA indicator was utilized to calculate the relative advantages of seven types of patented technologies within the five major science and technology powerhouses. The results of this analysis indicate that: China has three types of energy with relative advantages in patented technologies (RTA $\geqslant$ 0.9), in the order of solar energy, wind energy, and geothermal energy. The United States has six types of advantageous energy technologies, in the order of biomass, hydrogen, nuclear energy, solar energy, geothermal energy, and wind energy, in which the biomass, hydrogen, nuclear energy, and patent advantages are also ahead of the other four countries. South Korea has four types of advantageous energy technologies, in the order of ocean water, solar energy, wind energy, and geothermal energy. The United States boasts six predominant energy technologies: biomass, hydrogen, nuclear, solar, geothermal, and wind. Among these, biomass, hydrogen, and nuclear lead the other four countries in terms of patent superiority.

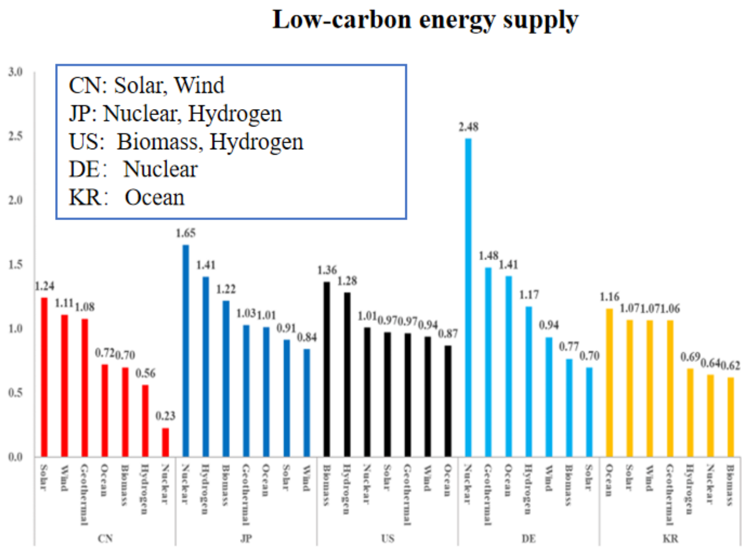

Figure 8. RTA of Low-carbon energy supply in key countries.

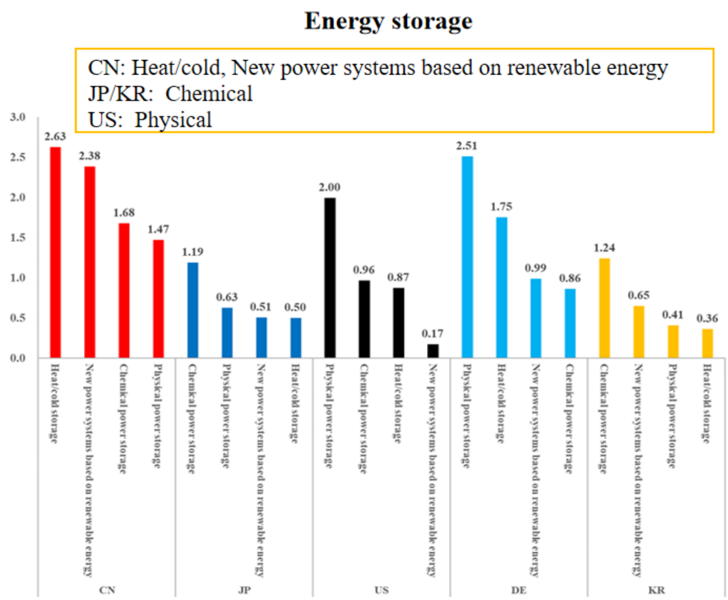

Figure 9. RTA of energy storage in key countries.

Multi-energy convergence potential detection

A patent-based technology convergence analysis has been conducted on seven significant domains of low-carbon clean energy technology: nuclear power and non-electric utilization of nuclear power, wind energy, solar energy, biomass energy, geothermal energy, ocean energy, hydrogen energy, and fuel cells. This analysis integrates the frequency of co-occurrence of technologies and the degree of technology relevance to identify key technologies, the degree of technology convergence within the field, and the future development trends in the domain of low-carbon clean energy.

(1) The number of co-occurrences of the seven energy patents is 3.44% (Table 5). The seven energy sources have few connections. There is not enough technological correlation between two of the seven energy sources, but wind energy shows a weak correlation with geothermal energy, ocean energy, solar energy, geothermal energy with solar energy, and hydrogen energy with biomass energy. It is more obvious when wind is combined with other energy sources.

(2) By measuring the correlation coefficient S_{ij} for n core technologies, a new n*n diagonal matrix can be obtained to demonstrate the proximity of the integration between core technologies (Table 5).

As illustrated in Table 5, the low-carbon clean energy technology combinations that demonstrate a certain degree of correlation between the patented technologies include wind energy-geothermal energy, wind energy-ocean energy, wind energy-solar energy, geothermal energy-solar energy, and hydrogen energy-biomass energy. When these findings are considered in conjunction with the scale of the number of patents, they serve to further substantiate the significance of wind energy in the development of multi-energy technology integration.

(3) The study takes the knowledge map of wind energy integration with other energies as an example (Fig.10). Wind energy, based on the photovoltaic effect, has a high degree of fusion with solar energy, which is mainly used for wind power generation and propulsion, as well as combinations with geothermal energy, ocean energy and nuclear energy. One of the most prominent directions of integration is the generation and propulsion of wind energy, which is based on the generation of power by mechanical means. Since the regions that are rich in wind energy are also likely to be rich in solar and geothermal energy, the possibility of their fusion association is higher. There is also integration with nuclear power.

Table 4. The co-occurrence of seven types of energy patents.

	Nuclear	Wind	Solar	Biomass	Geothermal	Ocean	Hydrogen	Total	coexist number	% of coexist	Total number of field
Nuclear	-	18	143	2	8	3	588	762	740	0.56%	131903
Wind	18	-	9416	44	156	4555	790	14979	14273	8.41%	169721
Solar	143	9416	-	206	852	640	1560	12817	12014	2.86%	420490
Biomass	2	44	206	-	7	19	2308	2586	2485	2.71%	91742
Geothermal	8	156	852	7	-	132	55	1210	1067	8.65%	12333
Ocean	3	4555	640	19	132	-	305	5654	5239	13.78%	38011
Hydrogen	588	790	1560	2308	55	305	-	5606	5165	2.61%	198266

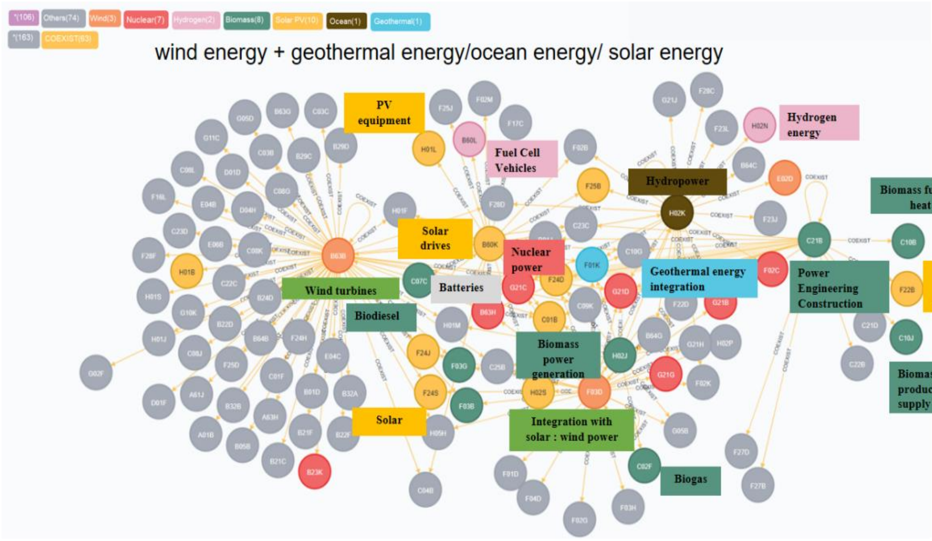

Figure 10. The case of Knowledge Graphs of wind and other energy convergence.

Technology Convergence Discovery and Evolution Analysis

Nuclear energy is a reliable, carbon-free energy source that generates a stable, continuous supply of electricity. In order to further analyse the evolutionary path of technological convergence, the convergence in the field of nuclear energy is selected as case study. The study is divided into five time periods: 1996-2000, 2001-2005, 2006-2010, 2011-2015, and 2016-2021. The co-occurrence network of convergence technologies in each period was extracted (Fig.11), the co-occurrence network of countries and technological field was analysed, and the development path of fusion technology was analysed. As shown in Figure 27, the number of patent applications in the field of nuclear energy has increased steadily with small fluctuations, peaking in 2004, 2012, and 2018, respectively. The number of IPC classification numbers related to nuclear fusion technology has been steadily increasing, indicating the continuous absorption of new technologies. Overall, the technology network was relatively isolated in its early years (1996-2000). However, as the 21st century progressed, the technical and functional network was gradually improved, and fusion trends began to emerge. The United States and Japan are leaders. In the last five years (2016-2021), China has joined in, forming a triad.

The United States and Japan have a clear first-mover advantage in the development of patented technology convergence in the field of nuclear energy. Since 2011, China has witnessed a substantial surge in the number of patents related to nuclear energy technology, which have begun to occupy a central position in the evolutionary network of fusion technology. In the past five years (2016-2021), China, the United States, and Japan have further solidified their dominance in this field. When considering China's historical context of related planning, the role of policy as an incentive for innovation becomes evident. Since 2005, China's "Eleventh Five-Year Plan" has promoted the development of nuclear power policy from "moderate development" to "active development." In 2006, China initiated the process of third-generation nuclear power autonomy. In 2011, China introduced the "Medium- and Long-Term Development Plan for Nuclear Power (2011-2020)," which adjusted the development goal to 58 million kilowatts of installed nuclear power in operation by 2020, with 30 million kilowatts of nuclear power under construction.

As illustrated in Fig. 11, the progression of patented nuclear energy technology fusion follows a technological trajectory that primarily involves the conversion of energy between nuclear, thermal, mechanical, and electrical domains. In terms of technology categories, batteries and their manufacture (H01M and its subordinate branches), chemical or physical methods and devices, such as catalysis, colloid chemistry (B01J and its subordinate branches), have been almost throughout the entire process of nuclear energy fusion technology evolution, suggesting that they are the basic and key technologies in the field of nuclear energy technology fusion. Metal compounds (C01G), electrolytic processes to produce compounds or non-metals (C25B), alloys (C22C), engines (F03G), ion implantation or chemical vapor deposition (C23C), and so forth, have played a significant and innovative role in the fusion of nuclear energy and other energy sources at various points in time, propelling technological turnover. This demonstrates that nuclear energy's function extends beyond mere electricity supply, encompassing the production of hydrogen, district heating, desalination, and numerous other nuclear technologies. It demonstrates that nuclear energy's function extends beyond the provision of electricity, encompassing diverse non-electricity-related applications such as hydrogen production, district heating, and seawater desalination.

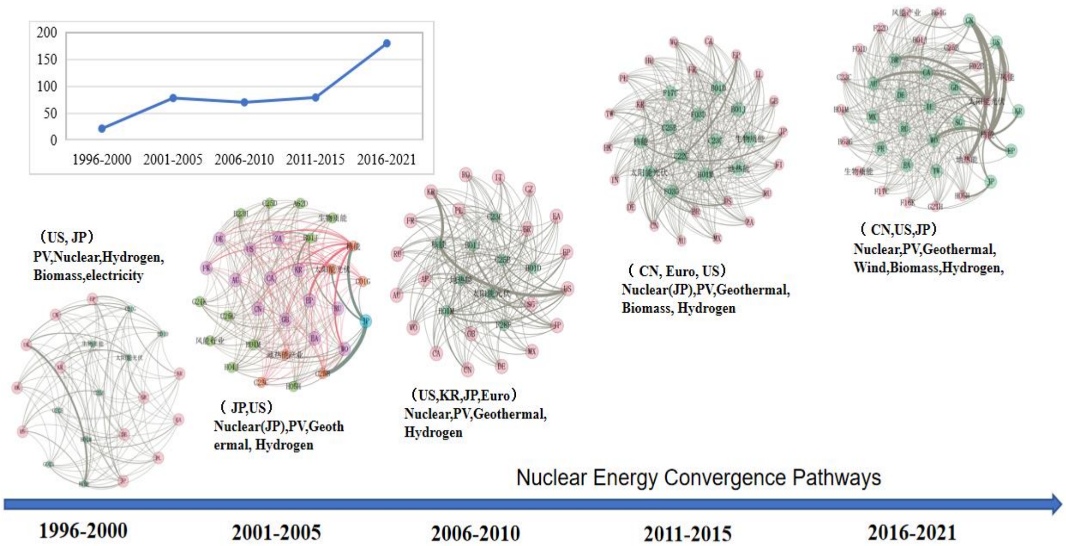

Figure 11. The Nuclear Energy Convergence Pathways.

In essence, the primary characteristics of the development of nuclear energy technology integration and innovation path performance can be delineated as follows: In the initial phase, the emphasis was placed on the augmentation of primary energy, with nuclear energy serving as a reliable power source. The technological innovation agenda centered on nuclear energy and renewable energy coupling technologies and facilities, including, but not limited to, small nuclear reactors and centralized solar thermal power plant technology. In recent times, the emphasis has shifted towards enhancing energy efficiency, with a particular focus on nuclear energy and renewable energy synergistic smart systems. Technological innovation has centered on the power system as the core, leveraging smart grids, with nuclear energy and renewable energy serving as the primary sources, complemented by an appropriate amount of hydropower and thermal power. This approach aims to facilitate the complementarity of cold, heat, gas, water, electricity, and other energy sources, thereby enhancing the efficiency of energy utilization. (iii) The present focus is on the expansion of the application of multi-energy fusion technology, with attention given to technological innovations related to nuclear energy for hydrogen production, such as large-scale nuclear energy for hydrogen production and secondary energy production.

Discussion & Conclusions

This paper proposes a domain knowledge discovery method based on convergence perspective, which can reveal domain knowledge reserve dynamics, technology opportunity insight and domain convergence technology evolution path. The method can help researchers, enterprises and government departments to better understand the technological opportunities, key technologies and future development trends of field convergence, which is important for promoting innovation and development of related fields.

The Multi-Energy Convergence Patent Knowledge Graph (MEPKG) is a domain knowledge database that extracts the latest advances in domain knowledge and provides information on the potential for technology convergence and development trajectories. It also improves user search experience, search engines, and knowledge discovery. In this paper, based on the research issues of multi-energy convergence (research progress, convergence potentials, and convergence paths), we try to use the knowledge graph of multi-energy convergence patents to study the trends, convergence signals, potentials, and development paths of multi-energy integration. The empirical analysis reveals that the signals of technology convergence in the multi-energy field are relatively weak. At present, the technological links among the seven energy sources are not very significant, but the integration of wind energy with other energy sources is more obvious. Due to the fusion effect of multiple energy sources between scientific principles, its potential for future multi-energy convergence is huge. In terms of technology pathways, the focus is on multi-energy power generation and thermal efficiency utilization. Patent-based multi-energy knowledge mapping helps to detect weak signals of multi-energy technology convergence. The study of technology pathways for their convergence is currently dominated by multi-energy power generation and thermal efficiency utilization. It can also reveal the evolutionary path of convergence of individual energy sources.

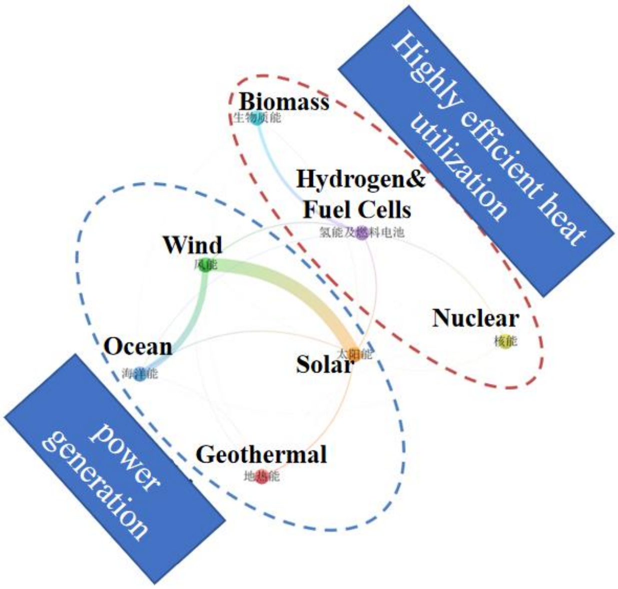

Figure 12. Multi-energy convergence directions.

However, the limitation of this paper is that the current research method is still based on structured data of patents. It is based on the fusion of the patent classification numbers, which belongs to a relatively elementary stage of the attempt. In the future, structured data and unstructured heterogeneous data will be further explored to further improve the research and application of knowledge graph on patent technology analysis. The knowledge mapping technology has great expansion potential in multi-domain and cross-domain to further improve data availability and data processing capability. Second, the boundaries between multi-domain and cross-domain are evolving with the dynamic integration of cross-domain, and future attention will be paid to the detection of opportunities for the integration of emerging technologies. In the future, we will continue to refine the method, expand the application areas, and improve the accuracy and efficiency of domain knowledge discovery. At the same time, we hope that the method will provide more valuable support and assistance to research and development in related fields.

There are several areas that require further exploration through research. Firstly, the automatic mapping model of multivariate technology classification categories necessitates the refinement of algorithms related to matching rules. Secondly, the indicators and algorithms for technology convergence discovery and path evolution analysis require enhancement, and the correlation with the knowledge graph must be strengthened. In future research, the application of the knowledge map of low-carbon and clean energy can be further strengthened, and the algorithms related to technology fusion path and evolution analysis can be improved through the use of algorithms related to the graph database.

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