Research on the Construction of Technology Co-opetition Network Based on Patents and Its Application in Industrial Analysis

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Abstract

Objective: This study constructs a technology co-opetition network based on patent data, which then reveals the competitive and collaborative relationships in the technological field. By analyzing the innovation characteristics and advantages of enterprises, industries, and regions, it provides important theoretical and practical guidance for technological innovation and industrial development.

Methods: The main research methodology of this study proceeds in three steps: "identification of technological competitors, construction of co-opetition network, and industrial analysis." This involves methods such as patent metrics, social network analysis, complex network analysis, as well as text analysis algorithms including natural language processing and similarity calculation.

Results: By constructing competitive-cooperative networks for the upstream, midstream, and downstream sectors, as well as for the segmented industries of the rare-earth permanent magnet industry, and by calculating data such as the competitive-cooperative coefficient, it is possible to conduct a targeted analysis of the current state of the industry. Incorporating multi-dimensional analysis that includes cities and industries not only reveals the competitive-cooperative status but also allows for targeted policy recommendations to local governments.

Limitations: This study has some limitations and shortcomings, such as the lack of uniformity in the indicators for relationships in the co-opetition network. That is, the current network analysis treats the co-opetition network as an unweighted network, but in reality, the network exists with different weight of competitive relation, cooperative relation, and potential cooperative relation.

Conclusions: This study provides a new method for industry analysis by delving into the content of patent texts and constructing a co-opetition network for industrial analysis. The method is highly operational and interpretable, allowing for its application in various fields of analysis.

Keywords: Patent Analysis; Co-opetition Relation Analysis; Text Similarity Recognition; Co-opetition Network Construction; Industry Analysi

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1. Introduction

As the global economy becomes increasingly competitive, technological innovation has emerged as the core driver of corporate and industrial development. Patent data, as a important source of information reflecting technological innovation, plays a significant role in analyzing industry technological trends, uncovering hotspots of innovation, and identifying opportunities for technological competition and cooperation. How to effectively utilize these patent data for industrial analysis has become an urgent issue to be addressed.

To date, many scholars both domestically and internationally have conducted research using patent citation structures, IPC classifications, and cooperative networks. However, few have analyzed the text content of patents. The title, abstract, and claims of a patent contain technical characteristics that are important for identifying innovative directions. This paper aims to recognize the competitive and cooperative relationships among technological innovation entities through the analysis of patent text content and to perform multi-dimensional industrial analysis by constructing a technological competitive-cooperative network.

The method of constructing a technological convergence network involves analyzing textual information such as titles and abstracts in patent data to calculate the technological similarity between patents. This process unveils the competitive and collaborative relationships among different enterprises and research institutions within the technological domain. Simultaneously, by examining the cooperative relationships among patents, insights into the collaboration scenarios between various entities can be gained, aiding in identifying potential partners for fostering mutual technological development.

In the realm of industrial analysis, technological convergence networks can be applied across various dimensions. Firstly, corporate convergence analysis assists in identifying partners and competitors, providing a deep understanding of the technological relationships between enterprises. This information becomes a basis for making informed strategic decisions. Secondly, through quantitative analysis of technological convergence networks, the innovation advantages of participants in the industry, including enterprises, universities, and research institutes, can be evaluated. This enables the optimization of industrial layouts and the enhancement of overall innovation capabilities. Finally, regional convergence analysis involves analyzing patent data from different cities to identify the innovation characteristics and competitive advantages of each city. This information serves as a reference for cooperation and competition between cities, promoting collaborative technological development between regions.

Constructing technological convergence networks based on patent data and applying them to corporate, industrial, and regional convergence analyses contribute to a profound understanding of the complexity and multi-layered nature of technological convergence. It provides scientific decision support for enterprises and governments, driving technological innovation, industrial upgrading, and regional collaborative development. This approach holds broad application prospects and offers new avenues for exploring information within patent data in the future.

2. Literature review

BRANDENBURGER A M et al. [1] first introduced the concept of "co-opetition" in 1996, suggesting that relationships between firms are not purely competitive or cooperative but rather involve a non-zero-sum game where both parties can achieve a win-win outcome. Subsequent scholars have extended and deepened the boundaries of this theory [2-5]. To delve into the analysis of co-opetition between firms, some scholars have used patents to identify technological competitors. Zhang Hudan [6] systematically explored and summarized the theories and specific methods of identifying technological competitors through patent network analysis, using CD-ROM patent data as a case study, and identifying competitors through citation networks and litigation relationship networks. Li Fangfang [7] constructed a dynamic model of technological competitors based on relative technological similarity, relative technological competitiveness, and time, and conducted empirical research on firms in the Chinese antidepressant drug sector to validate the model's effectiveness, feasibility, and superiority. Li Xiangyu [8] used patentometrics, innovation ecology theory, social network analysis theory, and positive-sum game theory to identify enterprise co-opetition relationships, analyze the evolution of these relationships, and explore the factors influencing enterprise relationships, thereby uncovering the evolutionary mechanism of enterprise co-opetition relationships.

Other scholars have analyzed the current state of industries through the structure and evolution of patent collaboration networks. Seyed Hessam Hoseinizade Mazlumi et al. [9] used social network analysis to study the structure of the Internet of Things patent network, analyzing the contribution network based on different international patent classifications, and then used social network analysis methods to identify key nodes and reveal the innovation paths in the Internet of Things. Ian Marques Ptoto Linares et al. [10] used network analysis of patents to understand trends and paths in technological innovation, connecting patents through citations to reflect the evolution of a technology and the most promising technological trends. Zhao Zhanyi et al. [11] conducted an analysis of the industry collaboration network structure and evolution in China's automotive manufacturing industry based on patents from applicants, applicant regions, and applicant types, revealing the changing patterns of collaboration clusters, regions, and modes among industry innovation themes, and providing suggestions for enterprise and government decision-making. Some scholars have also analyzed industry outcomes through competitive models. For example, based on the automotive industry, Xu Luyun et al. [12] constructed a knowledge network based on the structural characteristics of the patent knowledge network evolution, concluding that the knowledge network structures of enterprises under different categories show differentiated characteristics.

In summary, there has been a significant amount of research on industrial analysis based on patents, with methods mostly involving the construction of citation networks and collaboration networks. However, there have been limited attempts to establish competitive relationships between patents. Additionally, industrial analysis based on co-opetition theory has also been studied, but it is largely based on industry or known prior knowledge, with few attempts to mine competitive relationships between enterprises through patent content. Therefore, there is a current gap in research on mining competitive relationships through content, and this represents one of the issues that need to be addressed in the field.

3. Methodology

The main research methodology of this study proceeds in three steps: "identification of technological competitors, construction of co-opetition network, and industrial analysis." This involves methods such as patent metrics, social network analysis, complex network analysis, as well as text analysis algorithms including natural language processing and similarity calculation.

3.1 Co-opetition Relation Recognition

In the phase of constructing the co-opetition network, the first step is to identify the technological competition and collaboration relationships among the innovation entities within the industry. The main process is shown in Figure 1:

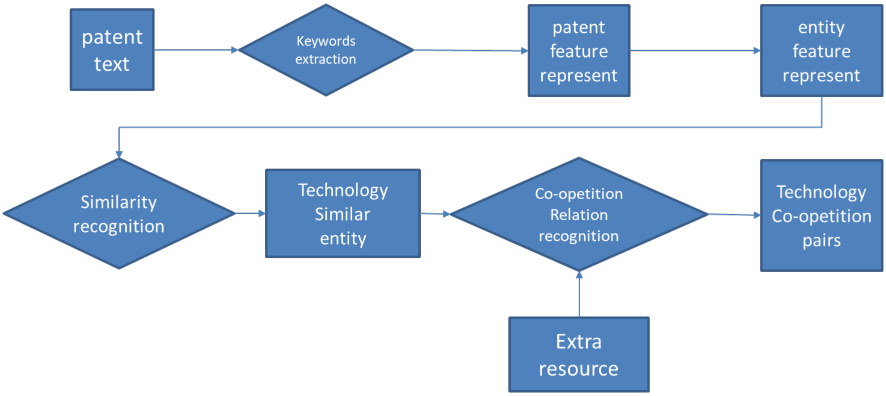

Figure 1. Methods for Identifying Technological Competitors

Firstly, text fields such as titles, abstracts, and claims need to be extracted from industry patents. Based on these text fields, keyword extraction is performed to represent the features of the patents. In this step, the keyword extraction process utilizes the maximum probability graph path segmentation of the ISTIC dictionary for text fields to ensure that words are extracted at the finest granularity. The text-rank algorithm is then applied to the segmentation results to obtain the feature representation of the patents.

Secondly, based on the external features of the patents such as patent applicants, the feature words and their weights for the innovation entities can be determined through weighting. Specifically, the feature representation of an innovation entity is equal to the pairwise sum of the feature words and their weights for all patents published by that entity. This method can fully describe the technological strength of an innovation entity at each technological point. Its advantage is that it takes into account all comprehensive research directions of the enterprise. Moreover, for very large technology entities with a wide range of involvement, their technological features will be more prominent in related directions and will not be weakened by normalization in terms of technological research and development capability representation.

Furthermore, after obtaining the feature representation of each innovation entity, text similarity calculation methods can be used to identify technically similar entities, with the main metric being the cosine similarity. Cosine similarity calculation, based on the angle between vectors rather than distance, is therefore not influenced by the magnitude of the feature values, making it suitable for texts of different lengths and sizes. Another important step in text similarity calculation is to reduce the number of candidate similarity pairs to increase calculation speed and efficiency. In this study, the HNSW method is used for efficient computation. Readers may also adopt methods such as SimHash and LSH to accelerate calculations. Since this is not the focus of the article, it will not be discussed further here.

Finally, external data and methods are introduced to identify competition and collaboration relationships. The external data introduced mainly falls into two categories: the first is co-publication relationships in patent data, meaning that if a patent is jointly applied for by two patentees, then the two patentees are not in a competitive relationship but rather have a technical collaboration. The second category is equity and investment relationships, indicating that if there are significant controlling interests, investment, and financing relationships between patentees, then the two patentees are also not in a competitive relationship and, while technically similar, are financially collaborative. Similarly, the external methods introduced primarily involve identifying the types of institutions, meaning that if the two entities with technical similarity are of different institution types, such as one being a business and the other a university or research institute, then there is no actual competitive relationship between them but rather the potential for industry-academia collaboration, which is defined as a potential collaboration in this study. For a technological competition and collaboration pair, if there is no technical or financial collaboration relationship, nor potential technical collaboration, then this study considers the two parties of the pair as each other's technological competitors.

3.2 Construction of Technology Co-opetition Network and Analysis Methods

After step 3.1, using patent text data combined with other external data, we can obtain three types of relationships: technical collaborators, potential technical collaborators, and technological competitors. Similarly, based on patent bibliographic data and other external data, combined with patent metrics, we can create an innovation profile of the innovation entities. For example, the number of patents can indicate technological innovation capability, and the address field of patents can be used to label patents with corresponding geographical tags. In the co-opetition network graph of technological entities, these elements can serve as node attributes in the graph construction, and the edges of the graph are composed of the three types of relationships，as shown in Figure 2.

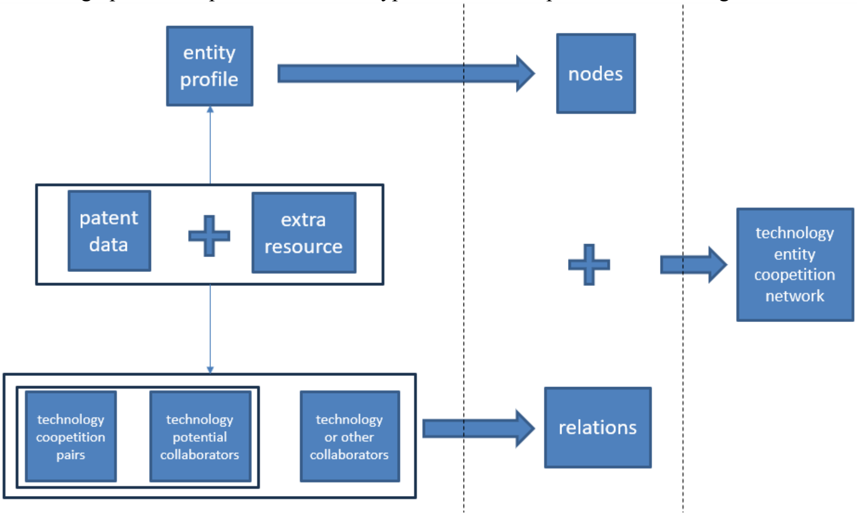

Figure 2. Method of Construction of Technology Co-opetition Network

Once the network is established, social network analysis (SNA) methods can be used to study the network structure. Social network analysis interprets the properties and dynamics of social networks by analyzing the relationships between social entities. For instance, centrality analysis (including degree centrality, betweenness centrality, closeness centrality, etc.) can identify key nodes in the network and measure the importance of individuals within the network; community detection (including modularity-based community detection methods, hierarchical clustering, etc.) can uncover closely connected groups of individuals within the network, enabling clustering and classification of the network; core-periphery analysis typically uses core-periphery models to identify the core and periphery regions of the network, where the core regions usually have higher density and connectivity. Additionally, there are role analysis, connectivity analysis, dynamic network analysis, and other methods. These analyses can reveal the intrinsic laws and characteristics of the technology co-opetition network, providing a basis for subsequent industrial analysis.

Visual analysis is also an effective method for network analysis. It converts the complex network's data structure into a graphical representation, allowing analysts to better understand the competition and collaboration patterns within the industry. In this study, network visualization is performed using layout algorithms based on VOS (Visualization of Similarities) and an improved Louvain clustering algorithm. Compared to traditional visualization methods such as force-directed graphs, the VOS layout algorithm performs well with large networks, effectively handling nodes in big data situations, and in the layout process, it ensures that nodes within clusters are close to each other while nodes from different categories are relatively farther apart. This clustering presentation helps to identify the main groups within the network and their relationships.

3.3 Methods of Industry Analysis

Industrial analysis mainly includes perspectives such as enterprise competition and collaboration analysis, industrial structure analysis, and regional competition and collaboration analysis. By analyzing the relationships of cooperation and competition among enterprises, the status and competitive advantages of different enterprises are revealed. Through the measurement of technological similarity and social network analysis, the innovative strengths and associations of participants in the industry are assessed. By analyzing the patent data published by cities, the competitive and collaborative relationships between cities and their dominant industries are calculated, providing insights into the internal innovation ecosystems of regions.

4. Results

The empirical analysis data used in this study comprises patents from enterprises across the upstream, midstream, and downstream of the rare-earth permanent magnet industry chain. Based on preliminary research by industry experts, a collection of 934 enterprises from 12 industries, including light rare earths, heavy rare earths, magnetic components, deep-processing equipment, samarium-cobalt permanent magnets, neodymium-iron-boron permanent magnets, high-abundance rare-earth permanent magnets, testing equipment, transportation equipment, household appliances, 3C electronics, and high-end equipment, was established. Their patents were retrieved from the China National Intellectual Property Administration(CNIPA) and filtered through IPC classifications and search terms, resulting in a total of 53,058 industry-related patents involving 266 cities.

4.1 Identification of Enterprise Competitive-Cooperative Relationships

In this study, Ningbo Yunsheng Co., Ltd. is taken as a case study to analyze its technological competitors, technological cooperation partners, and potential technological cooperation partners. The company is one of the world's largest manufacturers of rare-earth permanent magnet materials, with its business scope covering the midstream and downstream of the rare-earth permanent magnet industry chain, including neodymium-iron-boron permanent magnets, magnetic components, and high-end equipment. As of the end of 2023, the company has applied for a total of 185 invention patents, and after IPC screening for strategic emerging industries in new materials, 152 patents related to the rare-earth permanent magnet industry chain have been identified.

Firstly, based on the collection of rare-earth permanent magnet industry patents, a patent feature representation is formed for each innovation entity. Taking Ningbo Yunsheng Co., Ltd. as an example, its main feature words (top 10) are "magnetic steel, sintered neodymium-iron-boron magnet, magnet, neodymium-iron-boron magnet, component, sintered neodymium-iron-boron, neodymium-iron-boron, powder material, preparation method, motor". Secondly, the technical similarity between innovation entities is calculated using the feature representation. Finally, competitive, cooperative, and potential cooperative relationships are identified through methods such as co-authoring patents, corporate controlling relationships, and the category of research and innovation entities. The competitors, cooperation partners, and potential cooperation partners of Ningbo Yunsheng Co., Ltd. are listed in Table 1.

Tabel1. Top 5 Competitors, Cooperation Partners, and Potential Cooperation Partners of Ningbo Yunsheng Co., Ltd.

Technical Competitors	Competition Coefficient	Cooperation Partners	Cooperation Frequency	Potential Technical Cooperation Partners	Potential Cooperation Coefficient
Anhui Dadi Xiong New Materials Co., Ltd.	0.56	Nichikon (Ningbo) Motor Co., Ltd.	8	Liaoning University of Science and Technology	0.40
Ningbo Keti Magnetic Industry Co., Ltd.	0.53	Beijing University of Technology	2	Chongqing University of Technology	0.39
Beijing Zhongke Sanhuan High-	0.52	Ningbo Institute of Materials	2	Luoyang Institute of	0.39

Tech Co., Ltd.		Technology and Engineering, Chinese Academy of Sciences		Technology	
Jingci Material Science and Technology Co., Ltd.	0.52	Shanghai Institute of Ceramics, Chinese Academy of Sciences	1	Henan University of Science and Technology	0.39
Yantai Zhenghai Magnetic Materials Co., Ltd.	0.50			Xihua University	0.38

Through empirical analysis, it has been found that Anhui Dadi Xiong New Materials Co., Ltd., Ningbo Keti Magnetic Industry Co., Ltd., Beijing Zhongke Sanhuan High-Tech Co., Ltd., Jingci Material Science and Technology Co., Ltd., and Yantai Zhenghai Magnetic Materials Co., Ltd. are all companies with strong technological research and development capabilities in the NdFeB material industry, forming a technical competitive relationship with Ningbo Yunsheng Co., Ltd. Liaoning University of Science and Technology, Chongqing University of Technology, Luoyang Institute of Technology, Henan University of Science and Technology, and Xihua University are also involved in the field of sintered NdFeB and magnetic steel, and their size is suitable for industry-academia-research cooperation with Ningbo Yunsheng Co., Ltd.

4.2 Industrial Competitive-Cooperative Analysis

This study takes the NdFeB permanent magnet industry as an example to construct and analyze the industrial competitive-cooperative network. After preliminary expert investigation, there are 193 companies in the NdFeB permanent magnet industry. Through the identification of competitive-cooperative relationships among these 193 companies and the removal of some isolated nodes, the largest connected network is shown in Figure 3.

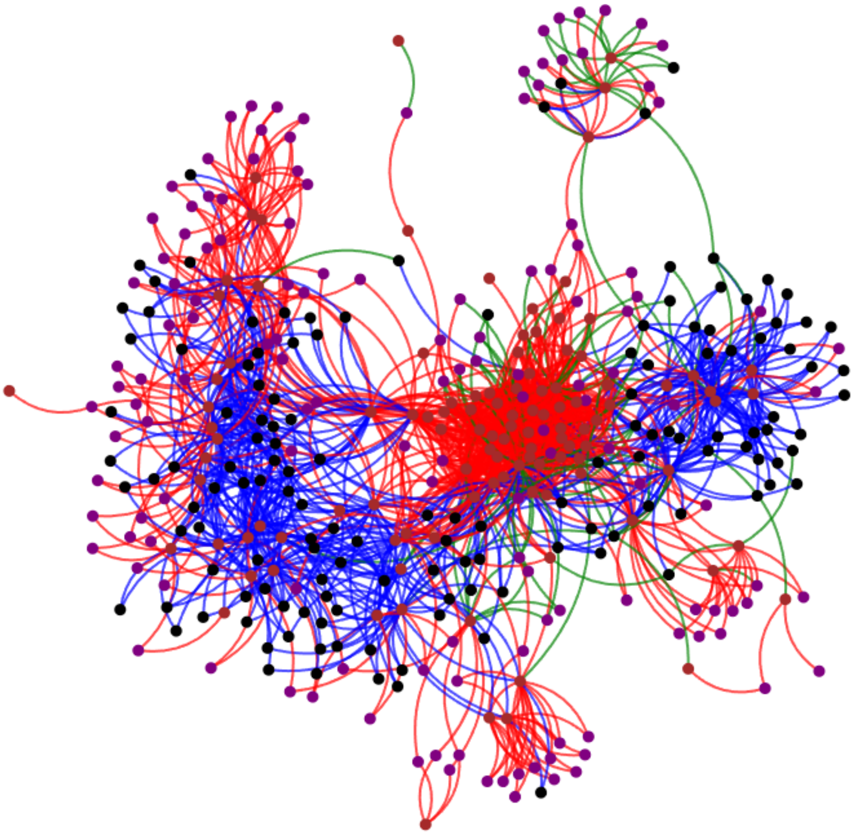

Figure3 NdFeB Permanent Magnet Industry Competitive-Cooperative Network

In the network, red nodes represent industry chain enterprises recommended by experts, black nodes represent universities and research institutes, purple nodes represent other enterprises, red lines represent competitive relationships, green lines represent cooperative relationships, and blue lines represent potential cooperative relationships. From the visualization, it is evident that a core group with strong competitive relationships has formed. Compared to competitive relationships, there are fewer cooperative relationships in the NdFeB permanent magnet industry, and most of them are concentrated between parent companies and their subsidiaries. There are many potential cooperative relationships, indicating a significant potential for industry-academia-research cooperation. The government can promote the transformation of scientific and technological achievements by encouraging enterprises to collaborate with relevant research universities and scientific research institutes.

Social network analysis is a commonly used method that employs graph theory and mathematical models to quantitatively analyze the structural attributes of social networks. In this study, this method is used to calculate common indicators such as network size, network position, network communities, and key nodes for the largest connected subgraph. Some of the indicator calculation results are presented in Table 2.

Table2 NdFeB Permanent Magnet Co-opetition Network Largest Connected Subgraph SNA Calculation Indicators

Network Global Indicators					
Number of Nodes	393	Number of Links	1830	Average Degree	9.312
Number of Industry Chain Companies	111	Number of Academic and Research	140	Number of Other Companies	142

		Institutions			
Number of Competitive Relationships	1127	Number of Cooperative Relationships	111	Number of Potential Cooperative Relationships	592
Node/Edge Importance Indicators					
Degree Centrality		Betweenness Centrality		Edge Betweenness Centrality	
Ningbo Yunsheng Co., Ltd.	0.165	Ningbo Yunsheng Co., Ltd.	0.146	(‘Shanghai Institute of Ceramics, Chinese Academy of Sciences’, ‘Hitachi Metals, Ltd.’)	0.068
Anhui Dadi Xiong New Materials Co., Ltd.	0.163	Tianjin Bangte Magnetic Material Co., Ltd.	0.135	(‘Ningbo Yunsheng Co., Ltd.’, ‘Shanghai Institute of Ceramics, Chinese Academy of Sciences’)	0.041
Beijing Zhongke Sanhuan High-Tech Co., Ltd.	0.145	Anhui Hanhai New Material Co., Ltd.	0.109	(‘Ningbo Yunsheng Co., Ltd.’, ‘Hangzhou Kode Magnetic Industry Co., Ltd.’)	0.030
Jingci Material Science and Technology Co., Ltd.	0.137	Hitachi Metals, Ltd.	0.078	(‘Shaanxi University of Technology’, ‘Ganzhou Futai Electronic Co., Ltd.’)	0.027
Yantai Zhenghai Magnetic Materials Co., Ltd.	0.135	Shanghai Institute of Ceramics, Chinese Academy of Sciences	0.071	(‘Tianjin Bangte Magnetic Material Co., Ltd.’, ‘Ganzhou Xinlei Rare Earth New Material Co., Ltd.’)	0.026

The global indicators of the network reveal that the connected network comprises 393 nodes and 1,830 relationships, with 111 industry chain companies, 140 academic and research institutions, and 142 other industry enterprises. The network has 1,127 competitive relationships, 111 cooperative relationships, and 592 potential cooperative relationships, indicating that there is a lack of substantial cooperation in the NdFeB permanent magnet industry and a large potential for industry-academia-research collaboration. The average degree of the network is 9.312, meaning that on average, a company is involved in 9.312 competitive or cooperative relationships, suggesting intense competition in the NdFeB permanent magnet industry.

The importance of nodes and edges in the network can reveal the key players and relationships. Ningbo Yunsheng Co., Ltd. has the highest degree centrality, indicating its greatest influence in the network. This is related to the long industrial chain layout of Ningbo Yunsheng Co., Ltd. in this field. The betweenness centrality characterizes the influence of nodes in network propagation, and Tianjin Bangte Magnetic Material Co., Ltd. and Anhui Hanhai New Material Co., Ltd. play a significant role in connecting the network. The edge betweenness centrality shows that the Shanghai Institute of Ceramics, Chinese Academy of Sciences, and Hitachi Metals, Ltd. have the highest influence, and these institutions have the strongest betweenness centrality.

After research, it was found that Japan is the country with the most NdFeB patents globally, and Hitachi Metals, headquartered in Tokyo, is an advanced enterprise in the global production technology of NdFeB permanent magnets, with over 600 sintered NdFeB patents. The NdFeB permanent magnet material industry has long been controlled by companies like Hitachi Metals, TDK, and Shin-Etsu Chemical through patent technology. The Shanghai Institute of Ceramics, Chinese Academy of Sciences, has connected these two companies through technological cooperation, becoming a key relationship in the technology competitive network.

4.3 Regional Competitive-Cooperative Analysis

Since patent publications have the external feature of the patentee's city, regional technological representation can be obtained through the patents published in that industry. This allows for the analysis of regional technological innovation themes, the comparison of strengths and weaknesses between regions, the main competitors and cooperation partners between regions, and more. Taking the NdFeB permanent magnet industry in Ningbo as an example, the main technological innovation points are concentrated in the directions of "sintered NdFeB, bonding preparation, film preparation," etc. Significant technologies can be chosen for breakthroughs, such as the industrialization of sintered NdFeB one-time molding technology, key technologies for the industrialization of high-performance bonded NdFeB magnets, and surface protection technology for rare earth permanent magnetic materials.

The main similar regions for Ningbo's technological themes are Beijing, Hefei, Jinhua, and Yantai. After research, it was found that there is only one NdFeB permanent magnet company, Ningbo Yunsheng Co., Ltd., in Ningbo, while there are more in cities like Beijing and Hefei. Ningbo's industrial development policy in the NdFeB permanent magnet direction can mainly refer to these industrial regions and cultivate leading enterprises to assist in the development of industrial clusters.

In the NdFeB permanent magnet industry, Ningbo's main cooperation partners are located in Beijing, Baotou, and Hangzhou. The cooperation mainly focuses on Ningbo Yunsheng Co., Ltd.'s subsidiaries, listed companies represented by Zhongke Sanhuan Co., Ltd., and research institutes represented by the Iron and Steel Research Institute. In the future industrial policy, it is necessary to further strengthen cooperation with upstream rare earth resource enterprises, universities and research institutes with corresponding R&D capabilities, and promote the extension of the industry to downstream applications.

5. Discussion & Conclusion

This study has constructed a technology co-opetition network based on patent data, and through multi-dimensional analysis, it has delved into the network characteristics of technology competition and collaboration and their applications at different levels. Through these analyses, the following conclusions are drawn:

Firstly, the construction of a technology co-opetition network is an effective method for studying technology competition and collaboration relationships. By processing patent text data and calculating technological similarity, a network reflecting technological associations can be constructed, revealing the complex relationships of technology competition and collaboration.

Secondly, the integration of external features into the technology co-opetition network is of significant value for industrial analysis. Based on the co-opetition network of industrial innovation entities, the innovative strengths and status of participants in the industry can be assessed, providing strategic analysis for enterprises within the network, promoting knowledge dissemination and academic exchange among universities and research institutes, optimizing the allocation of resources such as researchers, equipment, and funding, and providing a basis for finding suitable enterprises for technology commercialization, thus promoting industry-academia collaboration.

Lastly, the integration of external features in the technology co-opetition network provides new perspectives and methods for industrial and regional competition and collaboration. Government and decision-making departments can use the co-opetition network to understand competitive and collaborative relationships within the industry, formulate industrial policies, promote regional collaborative innovation, optimize resource allocation, understand industry risks and vulnerabilities, and thereby enhance the overall competitiveness and robustness of industrial clusters and promote international competitiveness.

There are some limitations and shortcomings in this study. For example, the relationships within the co-opetition network were not unified in terms of indicators; that is, the current network analysis treats the co-opetition network as an unweighted network, but in reality, the network is influenced by the intensity of competition, cooperation, and potential collaboration. Future work can focus on constructing and analyzing the technology co-opetition network as a weighted network to enrich the theory of competition and collaboration relationships. Additionally, from the perspective of industrial analysis applications, more uses for co-opetition network analysis can be explored.

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