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Evolution mechanism and empirical analysis of innovation network in advanced manufacturing industry

Mecanismo de evolução e análise empírica das redes de inovação na indústria transformadora avançada

Jianbo WANG[1,2] 0000-0002-2658-808X

Xing CAO[2,3] 0000-0003-4519-4913

Jingying ZHU[2] 0000-0001-6090-0623

Hui MA[3*] 0000-0001-7035-5761

Abstract

As the "chaotic" edge of innovation system has strong innovation potential and is easy to form and develop the emerging technology innovation network, the formation process of emerging technologies and their relationship with the development trajectory of original technologies are analyzed, and the evolution mechanism of innovation network of advanced manufacturing industry is deeply studied combined with life cycle theory. Firstly, empirical analysis is carried out by collecting patents data in the industrial robotics field. Then, the IPC co-occurrence network and patentee citation network are plotted by combining patents citation analysis with social network analysis. Next, the technical characteristics and knowledge flow characteristics of an advanced manufacturing innovation network are verified by calculating various indicators of the network. Finally, the empirical results show that the technology structure in the field of industrial robotics has high heterogeneity, wide integration among technical fields, and knowledge flow network has a small-world effect, characterized by easy flow, wide flow direction, high efficiency, fuzzy network boundary, and numerous and diversified core the key players in innovation.

Keywords: Advanced manufacturing industry. Evolution mechanism. Empirical analysis. Innovation network.

Resumo

As margens do "caos" do sistema de inovação têm um forte potencial de inovação e facilitam a formação e o desenvolvimento de redes de inovação em tecnologias emergentes. Em combinação com a teoria do ciclo de vida, o processo de formação de tecnologias emergentes e sua relação com a trajetória de desenvolvimento de tecnologias pré-existentes são analisados e o mecanismo de evolução das redes de inovação na indústria transformadora avançada é aprofundado. A análise empírica foi realizada através da coleta de dados sobre patentes na área de robôs industriais, utilizando a avaliação de citação de patentes combinada com a análise de redes sociais para mapear a rede de coatualização do IPC e a de citação de titulares de patentes e para verificar as características técnicas e de fluxo de conhecimento da rede de inovação de fabricação avançada calculando os indicadores da rede. Os resultados empíricos mostram que: as redes de fluxo de conhecimento têm um efeito de pequeno mundo, apresentam características de fácil fluxo, fluxo amplo, alta eficiência, fronteiras de rede ambíguas e um núcleo de temas de inovação numerosos e diversificados.

Palavras-chave: *Indústria transformadora avançada. Mecanismo de evolução. Análise empírica. Redes de inovação.*

[1] Hunan University of Humanities, Science and Technology. Loudi, 417000, China. *Correspondencia para*/Correspondence to: J. WANG. E-mail: wangjianbo@csu.edu.cn

[2] Business School of Central South University, Changsha, China

[3] Hunan First Normal University. Changsha, China.

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Introduction

In developed countries and regions of the world, the transformation and upgrading of advanced manufacturing industry are regarded as a strategic measure related to the national economy and national security, because advanced manufacturing industry is a high-end part of the manufacturing industry chain and value chain and has a great impact on national economy, industry and management activities. Therefore, it has become an urgent problem to explore the path to promote the innovation and development of emerging technologies, promote the independent innovation capability of advanced manufacturing industries and achieve key technological breakthroughs.

Emerging technologies change the existing technology ecosystem through combination and nonlinear evolution in their evolution process, and make inter-technological convergence more common and the technology boundary fuzzy by actively or passively exchanging various innovative resources with other organizations, which leads to more frequent knowledge exchanges (Klaus, 2016; Lv; Xiu, 2020). The cross-integration between different technology chains is likely to form breakthrough new technologies and more new technology chains (Huang *et al*., 2017), thus changing the structural characteristics of existing innovation networks. Gutowitz and Langton (1995) found that a system environment conducive to innovation usually tends to be close to the "chaotic edge", i.e. the equilibrium system space between too many rules and too few rules. They explained the characteristics of various networks by using three physical states: gaseous, liquid, and solid, and concluded that in the liquid environment, high-density connections are formed between network elements, and network resources are highly mobile, which is beneficial to the development of adjacent possibilities. New connections are formed through frequent and free combinations among molecules, and the environment in which the new connections are formed is relatively stable. The generated new connections cannot be easily damaged, and the stable flow environment can preserve the newly generated useful connections for a long time. Coupled with the information spillover, innovation will continue to spread in the system and further nurture and stimulate more innovation activities. Once the "liquid" network is formed, innovations and inventions will continue to emerge (Steven, 2012). The diffusion of knowledge, information, and other resources between different industries provides conditions for the integration of technologies, which leads to the gradual disappearance of barriers to technology entry, the fuzziness of technology boundaries, and finally the emergence of industrial integration (Cativelli; Pinto, 2020; Zhao; Li, 2017).

As the structure of emerging technological innovation networks changes, innovation networks gradually exhibit features such as fuzzy network boundaries, flexible network connectivity, heterogeneous key players in innovation, and easy flow of knowledge resources, while emerging technological innovation networks show a trend of boundary convergence. Therefore, in this paper, the evolution mechanism of innovation network in advanced manufacturing industry is analyzed in depth based on a case study of industrial robotics technology, the patent analysis, and social network analysis are used to carry out empirical research, which will enrich the research of emerging technology and innovation network theory, and have important theoretical and practical significance to stimulate the potential of technological innovation.

Evolution mechanism of innovation network in advanced manufacturing industry

Evolution of emerging technologies

The formation of emerging technologies is the complete replacement of old technological paradigms with new ones. Continuous change generally refers to the development of a technological paradigm along a certain track, while discontinuous change is usually accompanied by new technological paradigms, that is, the emergence of a new technological paradigm interrupts the development track of the original technology in its technological paradigm framework and jumps to a new technological development path, which is usually shown as jumping from one technology S curve to another.

The life cycle of emerging technologies during evolution is generally divided into the germination period, growth period, maturity period, and recession period (Foster, 1986; Lv; Song, 2020). When technology is developed to the growth stage, i.e. when the original technology reaches point A, the original technological path changes due to the absorption of new external knowledge or technological convergence, thus forming a new technological development path, as shown in Figure 1, emerging technology 1. When technology is developed from a growth period to a maturity period, i.e., the original technology reaches point B, the original technology has a key competitive advantage, but also enters the limit of technological development, and evolves due to the addition of new knowledge and resources or the recombination with other technologies, thereby forming new technology advantages, further improving the limit of technological development, and shortening the time of technological upgrading, as shown in Figure 1, emerging technology 2. When technology is developed into a recession, i.e. the original technology reaches point C, the original technology evolves from a recession to a growth period due to the addition of new knowledge resources in the innovation network, prolonging the life cycle of the technology, as shown in Figure 1, emerging technology 3.

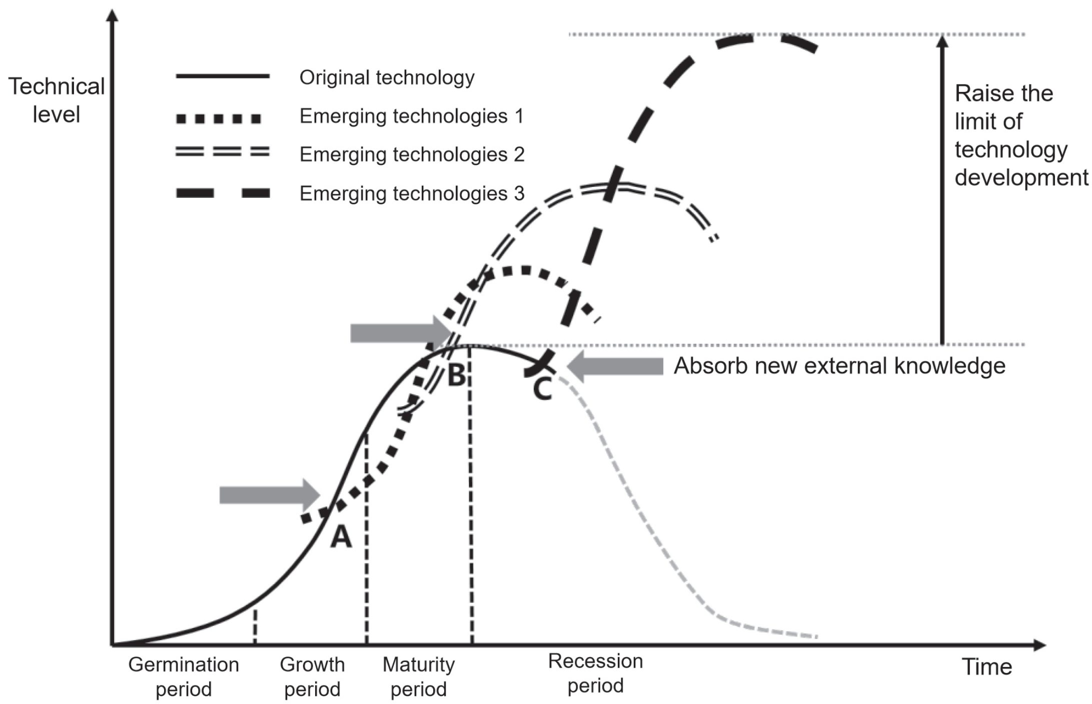

Figure 1 - Evolution process of emerging technologies.
Source: Elaborated by the author (2021).

Composition of innovation network and characteristics of knowledge flow in advanced manufacturing industry

Cluster innovation is a process in which enterprises in a cluster continuously acquire knowledge from their formal and informal relationship networks and integrate them. The main bodies of equipment manufacturing clusters form a variety of close relationships due to mutual communication and contact, which helps improve the innovation ability and has significant network characteristics (Fan *et al*., 2017). Equipment manufacturing cluster innovation network is a long-term and relatively stable form that can promote innovation within the cluster through mutual communication and exchange between enterprises and related institutions in a specific regional social and cultural background.

1) Main bodies of advanced manufacturing innovation network and knowledge resources between them.

Advanced manufacturing technology innovation network is a collection of knowledge base, innovative actors, and association rules. In other words, various actors form a certain network structure or mode by establishing various formal or informal connections, aiming at the production of advanced manufacturing science and technology knowledge, the development of technology and products, and the diffusion and adoption of innovation. In this cross-cutting field of frontier science and emerging technology, the innovation subject is more dependent on the science, technical knowledge, information, and resource supplement obtained by external connections. Therefore, networked innovation events are more common in the field of advanced manufacturing technology. According to different actors and association rules, there are different types of innovation networks, including cooperative innovation networks, scientific co-authored networks, technology networks or knowledge networks, which are also the main networks involved in this study. In addition, there are networks in the form of innovation alliances and innovation clusters, as well as networks of users and producers in specific departments.

The problem of optimal utilization of distributed knowledge is caused by the arrival of knowledge economy, which will be encountered within any complicated social system because the arrival of knowledge economy increases the intensity of product knowledge, which makes it more and more necessary to combine different distributed knowledge from different sources. In the emerging technology industry, product knowledge is distributed among different manufacturing enterprises in the industry and deepened in a specific field. But when the whole product is produced, it can be integrated with each other. Therefore, the high complementarity of innovation resources is very obvious in the high-tech industry (Li; See; Chi, 2019). From another point of view, emerging technology enterprises generally look at two important influencing factors: cooperation complementarity (complementarity of technical resources and organization and management) and technical leadership when choosing cooperative innovation partners. Generally speaking, the more complementary the technical resources of the parties involved in the technological innovation network, the greater the performance of the technological innovation network.

2) Node elements of innovation network in equipment manufacturing industry.

The node elements of innovation network in equipment manufacturing industry mainly include enterprises, universities/scientific research institutions, intermediary service institutions, and the government. Different from the general cluster innovation network, the center and main body of the equipment manufacturing cluster innovation network are the leading enterprises in the cluster, with a large number of small and medium-sized enterprises and supporting enterprises gathered around. Due to the high technical content of the equipment manufacturing industry, although some large leading companies have mastered a large number of leading technological advantages through introduction, digestion, and absorption, they must have their own proprietary knowledge in order to obtain sustainable competitive advantages (Tangen; Cashwell, 2016). To this end, some large leading companies have also established long-term cooperative relations with universities, research institutes, and vocational and technical schools inside and outside the cluster to expand their technological research and development capabilities and enhance their independent innovation capabilities. Equipment manufacturing industry is a highly capital-intensive and policy-oriented industry, so the government plays an important role in the cluster innovation network, which can not only help the enterprises in the cluster to win more national and provincial-level projects, but also provide various policy support for the cluster enterprises, improve the cooperation and social cooperation level of the cluster subjects in the region, and ensure the efficient transfer of knowledge and information in the cluster.

3) Relationship connection of innovation network in equipment manufacturing industry.

Similar to the general cluster innovation network, the relationship connection between the subjects include both formal cooperation agreements and informal exchanges and communication. With the increasing of relationships between the subjects, the connection can be strong or weak (Dronov; Evdokimov, 2018). In addition to the relationship connection of the industrial chain model, there is also a strong competition-cooperation model relationship connection between cluster enterprises. Due to the differences in enterprise scale and capability, the flying geese mode is usually formed with large enterprises as the core, medium-sized enterprises as the second echelon, and small enterprises as the auxiliary. The competition among cluster enterprises is mainly manifested in the competition for market and resources among enterprises at the same level. In general, if a cluster has a low number of leading enterprises, they will not have strong competitive relationships with each other, but mainly prey on external markets and resources from other similar enterprises outside the cluster. Moreover, in order to reduce costs and gain a competitive advantage, they have formed a close supporting partnership with small and medium-sized enterprises in the cluster, that is, partnership.

Research Design

The empirical analysis is carried out in the formation process of the innovation network in advanced manufacturing industry, which is reflected in the evolution of the overall structural characteristics of the innovation network in each stage of the emerging technology development life cycle and the knowledge flow between enterprises in the network node to promote the emergence of innovation behavior. As an emerging technology in the field of intelligent manufacturing, an industrial robot is also key technology to support the development of advanced manufacturing industry. Therefore, in this chapter, industrial robot technology is selected as the case study object. By collecting patent data of industrial robots, the formation and evolution process of industrial robot technology and its technological innovation network are analyzed from the network level by using the IPC co-occurrence network, and the influence of network structure on knowledge flow is emphatically analyzed, which further verifies the relevant conclusions of knowledge flow.

IPC Data sources and IPC co-occurrence network analysis

1) Data sources.

Gartner Patent, as one of the important carriers of technical information and the largest source of technical information in the world, is characterized by novelty and practicality compared with other types of documents. Patents include patentee (i.e., key players in the innovation), technical association, cooperation relationship, citation information, *etc*., and have been widely used in the empirical study of innovation networks. In the emerging technology maturity curve published by Gartner, self-driving car technology is rated as one of the most promising emerging technologies. Therefore, in this paper, the patented data in the field of industrial robotics are analyzed to study the shape and evolution law of innovation networks in this field.

The data in this paper come from the IncoPat database, specialized in searching global patent literature information, which can provide functions of patent retrieval, patent information retrieval, patent statistical analysis, patent warning, patent monitoring, etc. The database covers 112 countries, organizations, and regions, including China, the United States, Japan, Germany, South Korea, the United Kingdom, France, Russia, the European Patent Office, the World Intellectual Property Organization, etc. The search strategy in this paper is based on keywords related to industrial robotics technology in the subject area (TIAB).The information retrieval expression is TIAB= (((industrial robot OR manipulator OR mechanical arm) AND (joint OR coordinate OR welding OR handling OR parallel OR sorting

OR assembling OR packing OR unpacking OR unloading OR cutting OR grinding OR polishing OR spraying OR palletizing)) OR ("industr* (robot* or manipulat*)" OR "automat* guid* veh*" OR AGV OR articul* (robot* OR manipulat*) OR SCARA OR Delta (robot* OR manipulat*) OR cartesian* coordinat* (robot* OR manipulat*) OR "cylindr* coordinat* (robot* or manipulat*)" OR weld* (robot* OR manipulat*) OR transfer* (robot* ORmanipulat*) OR pallet* (robot* OR manipulat*) OR sort* (robot* OR manipulat*) OR stamp* (robot* OR manipulat*) OR assemb* (robot* OR manipulat*) OR pack* (robot* OR manipulat*) OR unpack* (robot* OR manipulat*) OR cut* (robot* OR manipulat*) OR grind* (robot* OR manipulat*) OR polish* (robot* OR manipulat*) OR paint* (robot* OR manipulat*) OR parallel* (robot* OR manipulat*)))). The symbol * is used as a wildcard to retrieve the basic variant of a word cell as of December 31st, 2020. A total of 221,606 patents were obtained. The patentee names of enterprises and their subsidiaries with homonyms are merged, and the data is cleaned to form a data format that conforms to the import of Gephi and NetMiner4. The patent name, patent number, patentee, number and type of patentees, application date, patent citation information, and IPC classification information are mined from the data for multi-level and multi-dimensional in-depth analysis.

2) IPC co-occurrence network analysis

IPC co-occurrence network: The IPC co-occurrence network is used to analyze the interaction between different technical domains, where each node represents a technical domain and the connections between the nodes are co-occurrence relationships, i.e., two connected PC classifications appear in the same patent at the same time. The more nodes, the more fields of technology involved in representing the technology, the more connections, and the more co-occurrences are represented. The intensity of co-occurrence can reflect the degree of correlation between different fields of technology.

Patentee cooperative network: In the cooperative network, the nodes represent the key players in innovation, and the connections between the nodes represent the cooperative relationship among the key players in innovation, which is usually accompanied by the flow of tacit knowledge.

Patentee citation network. Patent citation reflects the relationship between patent literature and non-patent literature, the quality and influence of patented technology, the knowledge flow and knowledge spillover contained in patents, and also the direction, characteristics, and process of information flow guiding technological innovation (Stolpe, 2002). The patent citation network adopted in this paper is a network constructed by using the organization of patentees as the node and the citation relationships between organizations as the line to analyze the knowledge flow relationship between the organizations of patentees. The citation relationship is divided into forward citation and backward citation, the former refers to the case where the patent is cited by other patents, and the latter refers to the case where the patent refers to other patents. The Citation network is directed because of its directionality.

Analysis indicators: In this paper, the statistical indicators such as density, average degree, number of components, average path length, diameter, and clustering coefficient proposed by Albert and Barabsi (2001) are adopted, which have been widely used to analyze the structure and properties of the network, the network topology analysis indicators are as follows.

1) Indicators: Definition.

2) Number of nodes: Total number of nodes in the network.

3) Number of connections: Total number of connections in the network.

4) Density: The ratio of actual connections to all possible connections in the network.

5) Average degree: Degree is the sum of connections between a node and its neighboring nodes. The average degree is calculated by dividing the sum of all node degrees by the total number of nodes in the network.

6) Number of components: Components refer to independent subnets in the network, and the number of components represents the number of independent subnets in the network.

7) Number of nodes in the maximum component: Total number of nodes in the maximum component.

8) Average path length: Average path lengths between any pair of nodes in the network.

9) Diameter: Maximum path length in the network.

10) Clustering coefficient: The clustering coefficient of a node is the ratio of the actual number of links between neighboring nodes to the maximum possible number of links between them. The clustering coefficient of the network is the average of the clustering coefficients of all nodes.

In this paper, the indicators proposed by Freeman (1978) are used for centrality analysis to test the value and importance of each node.

1) Degree centrality: It is measured by the sum of nodes directly connected to a node, the degree centrality of node i is expressed as: $c(i)_d = \frac{\Sigma_k^n a(N_i, N_k)}{n-1}$, where $a(N_i, N_k) = 1$, if and only if $i(N_i)$ and $k(N_k)$ are connected, otherwise $a(N_i, N_k) = 0$. n is the total number of nodes in the network. In the case of directed networks, in-degree and out-degree centralities are defined.

2) Closeness centrality: It is measured by using the sum of the shortest path lengths between one node and all other nodes, with global centrality, including not only direct connections, but also indirect connections. The closeness centrality of a node $i(c(i)_c)$ is calculated by $c(i)_c = \frac{n=1}{\sum_{k=1}^n d(N_i, N_k)}$, where $d(N_i, N_k)$ is the path length between nodes $i(N_i)$ and $k(N_k)$, and n is the total number of nodes in the network. In directed networks, the closeness centrality is divided into in-degree and out-degree closeness centralities.

3) Betweenness centrality: $i(C(i)_b)$ $c(j)_b = \frac{\sum_{j<k} g_{jk}(i) / g_{jk}}{[(n-2)(n-1)/2]}$ g_{jk} gk $g_{jk}(i)$ ijkn

It is used to measure the degree to which a node plays the role of bridge or agent in the network, that is, the degree to which a node controls resource. Betweenness centrality of node is calculated by $c(j)_b = \frac{\sum_{j<k} g_{jk}(i) / g_{jk}}{[(n-2)(n-1)/2]}$, where g_{jk} is the number of paths between nodes g and k, and $g_{jk}(i)$ is the number of paths between nodes j and k connected by node i; n is the total number of nodes in the network.

IPC co-occurrence network analysis

In this paper, the evolution of knowledge flow involved in the most cutting-edge industrial robot technology is selected for research and analysis. The data in this paper comes from the IncoPat database.

In this paper, patent applications are divided into four window periods according to their number and growth trend over the years, and the IPC classification number co-occurrence network diagram is drawn to extract the maximal connected subgraph after removing weak connections as shown in Figure 2. The node size indicates the degree, and the bigger the node the greater the degree, while the thickness of the connection indicates the weight, and the thicker the connection, the greater the weight.

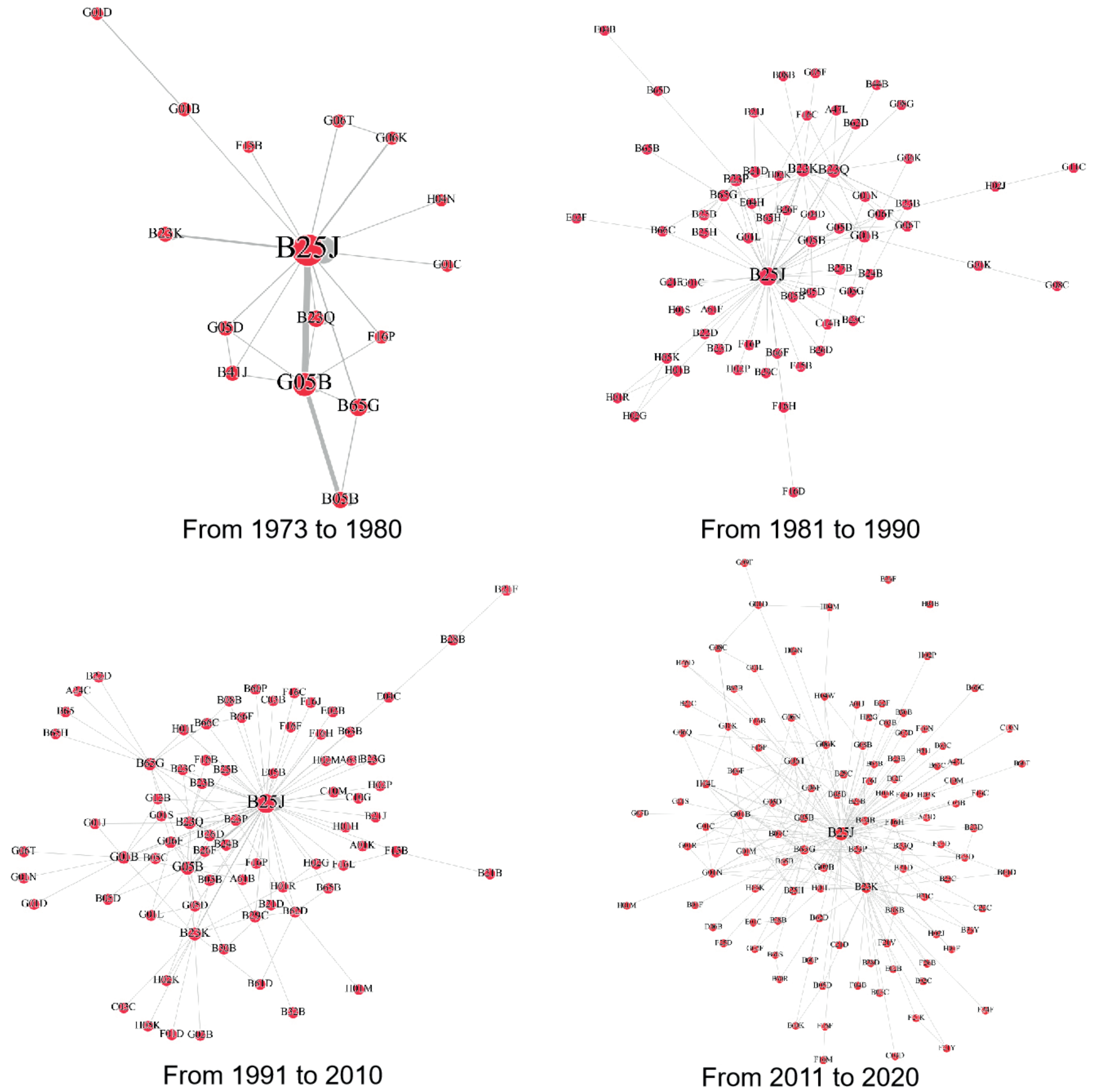

Figure 2 - IPC co-occurrence network diagram.
Source: Elaborated by the authors (2021).

IPC co-occurrence network analysis indicators at each stage are shown in Table 1.

Table 1 - Analysis of co-occurrence network indicators for industrial robots.

1 de 2

Indicators	1973-1980	1981-1990	1991-2010	2011-2020
Number of nodes	16	64	75	113
Number of connections (not authorized)	29	134	151	275
Density	0.242	0.066	0.054	0.043
Clustering coefficient	0.527	0.503	0.455	0.345

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Table 1 - Analysis of co-occurrence network indicators for industrial robots.

2 de 2

Indicators	1973-1980	1981-1990	1991-2010	2011-2020
Average degree	3.625	4.188	4.027	4.867
Average path length	2.983	2.556	2.448	2.475
Maximum component ratio	62.50%	60.93%	74.67%	78.14%
Average betweenness centrality	7.375	49.016	53.560	79.681
Average closeness centrality	0.522	0.404	0.420	0.407

Source: Elaborated by the authors (2021).

Analysis on Figures 2 and 3 shows:

1) The increasing number of fields of technology: The number of nodes in the network keeps increasing, from 16 in the first stage to 113 in the fourth stage. The network size has increased nearly sevenfold, showing an accelerated growth state. As a node represents a field of technology, it indicates that the technology of automatic industrial robots is gradually involved in more and more different fields of technology. As a whole, the technology network is rapidly integrating, absorbing external knowledge, and expanding.

2) The increase of technology convergence: In the network, the number of connections is increasing rapidly, and the co-occurrence types are also increasing, indicating that there are more and more fields of technology where convergence occurs. With the expansion of network size, the network density does not decrease, but remains basically unchanged, which shows that once the new technology enters the network, it can quickly connect with other technology networks. The average degree of the network indicates the average number of connections of each node to other nodes in the network. A larger average degree indicates that the number of fields of technology that have technology integration with a technology field is increasing, further indicating that the phenomenon of knowledge flow is becoming more and more frequent.

3) Enhanced network connectivity: Overall, the proportion of the largest network component is increasing from 62.50% to 78.14%, which indicates that different technologies converge to form a whole large network, so the average path length is also decreasing.

4) Reduced degree of the networking core: The network average betweenness centrality decreases continuously, indicating the role of nodes as intermediary bridges is weakened and technology convergence is no longer limited to certain key technologies. The significantly larger average closeness centrality indicates that the flow of knowledge among different technical fields is intensified and knowledge convergence is becoming more common.

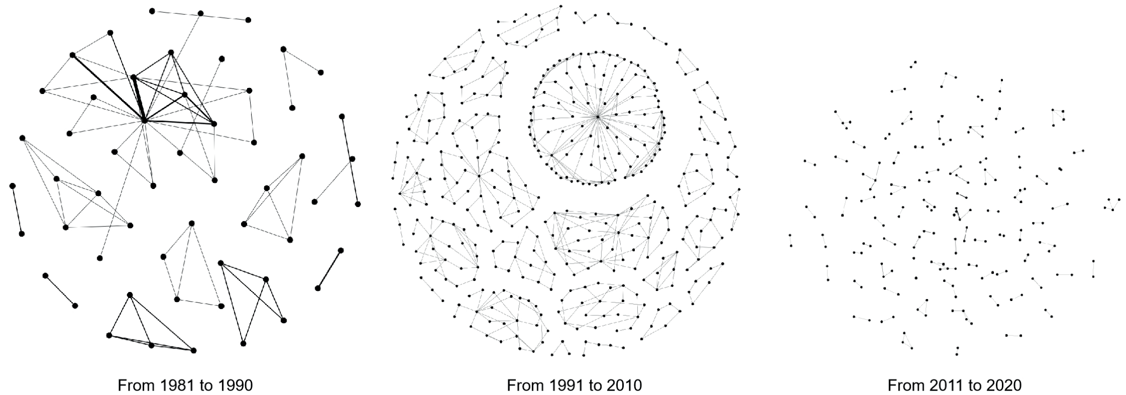

Figure 3 - Patentee cooperative network.
Source: Elaborated by the authors (2021).

The above analysis reveals that the trend evolution of industrial robotics technology conforms to the characteristics of diversified technology, high heterogeneity, and universal convergence under the situation of convergence of emerging technology innovation network technology.

Patentee cooperative network analysis

A diagram of the cooperative innovation network connected by joint patentee relations is drawn with the patentee as a node in four stages, as shown in Figure 3. No corresponding collaborative innovation network map is formed since there were essentially no joint patentees in 1980. Since 1990, the size of cooperation network in the field of industrial robotics has increased significantly, and the number of nodes and edges in the network has increased significantly, which indicates that cooperation among the key players in innovation in the field of industrial robotics has become more frequent in recent years.

Indicators of different networks are calculated according to four stages. Through comparative analysis, it is found that the structure of the overall network has changed significantly over time. For example, the evolution of these four stages conforms to the characteristics of network opening, expanding and fuzzy network boundary in the convergence of emerging technology innovation network technology.

As shown in Table 2, the size of the cooperative network has steadily increased, and the number of cooperative innovative subjects and cooperative relationships in the field of industrial robotics has significantly increased with the progressive development of cooperative innovation activities. The cooperative network is gradually opening. On the one hand, the gradual decrease of network density makes the industrial robot cooperative innovation network undergo the process of transition from high density to low density, and the network density is reduced from 0.049 to 0.006 step by step. On the other hand, the average degree and average clustering coefficient gradually decrease, the average path length and path dependence increase, and the degree of network aggregation decreases. During the period from 1981 to 1990, the subnets in a cooperative network were fully graphical, had rules of network structure, and close internal membership. Such regular networks are usually based on social or geographic connections. At this time, there are fewer key players in innovation in the network, but they have a high degree of aggregation and relatively stable interaction. Long-term cooperation facilitates the accumulation of technical knowledge in an area in the innovation network and makes it difficult for technical knowledge to spread out of the network.

Table 2 - Indicators for patent cooperative network for industrial robots.

Stages	1981-1990	1991-2010	2011-2020
Number of nodes	55	410	211
Number of connections (non-weighted)	73	528	127
Density	0.049	0.016	0.006
Clustering coefficient	0.846	0.632	0.444
Average degree	2.655	2.576	1.204
Average path length	1.594	3.418	1.29
Maximum component ratio	32.69%	4.89%	5.52%
Average betweenness centrality	2.058	48.176	0.249
Average closeness centrality	0.824	0.413	0.904

Source: Elaborated by the authors (2021).

Once the technical knowledge has accumulated to a certain extent and a breakthrough innovation has occurred, the network can build the initial technology chain. Therefore, the first two stages are the breeding stage of industrial robotics technology. From 2011 to 2020, network density further decreased, and aggregation decreased, which accelerated knowledge flow and diffusion in the network and promoted technology growth. The further increase of the number of the key players in innovation and cooperation relationship is conducive to promoting a large number of progressive innovations and promoting the extension of the technology chain outward. The evolution of these four stages conforms to the characteristics of network opening, expanding and fuzzy network boundary in the convergence of new technological innovation and network technology.

From the network membership composition, enterprises, foundations, colleges, and institutes are mainly involved in this cooperative network, in which the foundation acts as a bridge to connect different types of key plays in the innovation.

In terms of the strength of network memberships, it is easier for key plays in the innovation of the same type to establish stronger connections, which in turn promotes the transmission of tacit knowledge in cooperative relationships. Most of the patentees of enterprises have weak connections with individual patentees, and enterprises also establish cooperative connections with universities, institutes, and foundations through extensive weak connections, because weak connections facilitate access to heterogeneous resources, and enterprises as innovators will establish weak connections with other types of organizations to obtain different resources needed for innovation in order to carry out continuous innovation activities.

Knowledge distance plays a dual role in knowledge transfer between innovation network subjects. A small distance will make the profits from knowledge flow smaller and smaller, which will weaken the willingness to knowledge flow. With the development of technology and the increase in innovation subjects, regional and industrial restrictions will be gradually broken through. Geographical boundaries and industry boundaries will be further broken down as further requirements of innovation development.

Analysis of the citation network of patentees

Through the network topology analysis, the various indicators of the network cited by the patentee are obtained. The overall network consists of 268 nodes and 589 connections. The density is 0.101, the clustering coefficient is 0.458, the average degree is 4.177, the average path length is 2.366, the average betweenness centrality is 47.408, and the average closeness centrality is 0.438. The average path length of the network cited by the patentee is less than 3, which means that the average path length from one node to the other does not need 3 steps, which is much smaller than the predicted value of random network 7.398 proposed by Erdos and Renyi, indicating that the maximum path length of the network is also only 7, much smaller than the predicted value of ER model 13. The above fully demonstrates that patentees in the field of industrial robotics have a stronger small-world effect than ER model, indicating that the network can effectively flow, spread, and transfer knowledge. The average clustering coefficient is less than 0.05, much smaller than the theoretical predictions of ER model 0.006, which is consistent with the larger clustering of the real world proposed by Watts and Strogatz than that of random networks. The above analysis shows that the patentee citation network has a shorter average path length, diameter, and larger clustering factor than the ER model of the same size, indicating that the network has faster and more efficient knowledge mobility.

Degree centrality represents the degree to which a node is directly connected to other nodes. The size of the node degree reflects the degree of activity of the organization in the technical network and the greater node degree indicates more organizations exchanging knowledge with the organization. The out-degree represents the outflow and diffusion of knowledge, and the in-degree represents the absorption of knowledge. The closeness centrality is the sum of the shortest distance between a node and other points in the graph. The greater closeness centrality indicates the closer the point is to other points, the fewer intermediate nodes it depends on, and the easier it is to spread and absorb technical knowledge. The average closeness centrality in the network is larger, and the top ten organizations have little difference in closeness centrality values, indicating a wide and efficient flow of technical knowledge among organizations in the overall network. Betweenness centrality measures the degree of node control over resources and can be understood as the degree to which nodes act as bridges and intermediaries. The average betweenness centrality of all nodes is minimal, and there are no nodes with large betweenness centrality, that is, no organizations with strong betweenness centrality exist, which further illustrates that organizations have a close knowledge flow between each other, the flow is close, and the communication between each other does not need to be mediated by a specific medium.

According to the above analysis, the citation network of industrial robotics technology conforms to the characteristics of strong knowledge mobility and high aggregation of emerging technology innovation networks.

Conclusions and Enlightenment

In this paper, the mechanism of innovative network evolution in advanced manufacturing is explored, and the network structure and the characteristics of knowledge flow under the trend of cross-border integration of innovative networks are measured by constructing cooperative innovative networks based on patent information of industrial robotics from the Incopat database.

1) In combination with emerging technology evolution development, the mechanism of innovation network evolution in advanced manufacturing is proposed and analyzed. Several features of the evolution of structure and knowledge flow are analyzed at the network level, including heterogeneity, flexibility of links, strong network connectivity, fuzzy network boundaries as well as strong knowledge flow and convergence of technologies.

2) The IPC co-occurrence network, patentee cooperative network, and patentee citation network are constructed from patent data in the field of industrial robotics using patent analysis and social network analysis to analyze the technology convergence, and implicit knowledge flow, and explicit knowledge flow, respectively. Industrial robotics technology and its innovative network all present life cycle characteristics. With the development of industrial robotics technology, network connection relationship becomes closer and closer in the whole life cycle. With the acceleration of knowledge transfer behavior, the heterogeneity of nodes becomes smaller and smaller, and the knowledge potential difference increases during the adjustment period. Network centrality does not take shape until the innovation network adjustment period.

3) The innovative subjects of the innovation cooperative network of industrial robots have obvious structural characteristics, and the distribution of the breadth and depth of cooperation among innovative subjects is expanding continuously. There are different core innovative subjects in different stages of development. The characteristics of innovative subjects are closely related to the development of the industrial economy, and the scope and depth of cooperation in the field of technology are constantly expanding.

In this paper, the evolution mechanism and characteristics of innovation networks in advanced manufacturing industry are analyzed as a whole. Besides, only industrial robotics technology is analyzed. In the future, other types of emerging technologies can be analyzed, and individual enterprise networks can be constructed to further analyze the structural characteristics and knowledge flow characteristics of innovation networks in advanced manufacturing industry.

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Contributors

J.Wang, H.Ma, and X. Cao contributed to conception and design of the study. J. Wang and J. Zhu performed the data analysis and interpretation. All authors contributed to manuscript revision, read, and approved the submitted version.

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