

Research Article

Critical Nodes Identification of Scientific Achievement Commercialization Network under k -Core

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Aiming to improve the commercialization efficiency of scientific innovative achievements, this paper utilizes the time series visualization method to construct the time series network of each subsystem. After that, the network similarity is calculated by the cosine similarity theorem. On this basis, a new multilayer network adjacency matrix is obtained. With the adoption of k -core technology, the critical nodes can be identified to study the transformation efficiency of the innovation value in the network. Finally, according to the provincial innovation value transformation data of China from 1998 to 2016, an empirical study was carried out to calculate and analyze the transformation efficiency of innovation achievements in 30 provinces. The results indicate that (1) the transformation efficiency of innovation value can be expressed by the structure of the time series network constructed by the input-output vectors; (2) the mapping relationship of the value transformation vectors could be reflected by the cosine similarity of the time series network, while the transformation efficiency of innovation value could be identified using the k -core; and (3) the transformation efficiency of innovation value in three coastal provinces is relatively higher, while that of the rest of the provinces is roughly the same among the 30 provinces.

1. Introduction

Scientific innovative achievements play an important role in the development of social, economic, and industrial technology. Meanwhile, the commercialization efficiency of those innovative achievements is crucial in enhancing the core competitiveness, which has attracted the attention of numerous countries. Examples include the “Silicon Valley miracle” in the United States and the “Cambridge phenomenon” in the United Kingdom; our societies try to build some high-tech industrial clusters to speed up commercialization of scientific innovative achievements which is helpful for further social development. Hence, improving the commercialization efficiency and capability has already been employed as an important way to improve the national comprehensive strength, especially for most western developed countries.

Recently, China has greatly increased the economical and human-power investments in the development of scientific technologies, while the country has become an innovation-driven economical entity from an imitative latecomer [1]. However, with the flourish of scientific innovative achievements in China, the commercialization efficiency in China is relatively low and has become a bottleneck. There are problems such as insufficient funds for transformation, insufficient incentive policies, immature market demand for technology, and insufficient ability of researchers to directly participate in production and operation. Facing fierce international competition is becoming even more serious day by day, and the promotive effects seem to be limited if we continue to blindly pursue the rapid increase in the number of scientific innovative achievements. Therefore, it is necessary to deploy attention to improving the commercialization efficiency of scientific achievements

[2]. Furthermore, it is also very important to effectively evaluate the commercialization quality and efficiency, which is beneficial in guiding scientific research resource allocation.

Numerous researchers have devoted efforts to study the commercialization of scientific achievements from various fields, including theoretical research and industrial technology, even if it is a complicate process that is full of complexity and uncertainty. Bennett et al. [3] claimed that both suppliers and purchasers would benefit from the commercialization of scientific research achievements, while the purchaser should combine the purchased techniques and current commercial models to strengthen the core competitiveness. Zhang and Shi [4] proposed an evaluation index mechanism based on the innovation diffusion theory in order to identify the influential factors in the commercialization process. The fuzzy cognitive model is constructed through expert scoring to realize a dynamic simulation of a complex network system containing multiple causalities. Finally, the reciprocal relationship and interaction of the influencing factors of research achievement transformation are found.

Recently, complex network theory has emerged and been successfully applied to the analysis of complex systems, including socioeconomic systems [5–7] and ecology and biological systems. In a complex network, the topology consists of edges and nodes, while the relationships among nodes are indicated by edges. With the success of such a theory, numerous scholars have investigated the data-driven analysis of complex networks. Hu et al. [8] constructed the network from American power grid market data with the adoption of the visibility graph (VG) model and then conducted analysis of corresponding structural characteristics. Based on a revised VG model, Cui et al. [9] investigated the stock price network of China with the adoption of the complex network theory. Among the studies of complex networks, the identification of key nodes is an important research topic. Hu et al. [10] performed key organization analysis of terrorist organizations through the commercial right method and the centrality principle; Borgatti [11] proposed KPP-POS and KPP-NEG in order to identify the key nodes in social networks. Later, a single-layer complex network is extended to a multilayer one, as in [12]. A multilayer network consists of various types of nodes and corresponding relationships (including intralayer edges and interlayer ones) [13, 14]. In practice, multilayer networks can be utilized to characterize real-world complex systems [15]. For instance, integrated social platforms mimicking different social relations (friends, colleagues, relatives, etc.) integrated transportation systems (bus, subway, train, aircraft, etc.).

Thus, numerous studies have been conducted to investigate the topology, structure, and dynamics of the multilayer network. Bohnert analyzed the influence of friends' attitudes on individual drug abuse based on the multilayer complex network theory [16]. Bródka et al. [17] proposed a community detection method based on the multilayer edge clustering coefficient to tackle multilayer social networks, which consists of a large quantity of users' activity data in the IT system. Furthermore, Bródka et al. [18] investigated the multilayer

degree center of a multilayer social network. In their study, the multilayer social network is composed of ten different layers, which are constructed based on the data collected from the Web 2.0 website. Then, the network is analyzed through different centrality measurement methods. Magnani and Rossi [19] introduced a new model to represent an inter-connected network and then extended the traditional SNA method to deal with the diversity of networks. With the adoption of the “ k -core decomposition” method, Du et al. [20] encapsulated China Aviation Network (CAN) into a multilayer infrastructure which is decomposed into the core layer, the bridge layer, and the peripheral layer. Ding et al. [21] applied quantitative research methods to study the changing trend and related impact of multilayer network structure in urban dynamics detection. Paul and Chen [22] studied the problem of estimating a consistent community structure from multilayer combination information of multilayer networks based on spectral clustering or the low rank matrix decomposition method.

Based on the aforementioned studies, one may find that it lacks investigations which work on the transformation of research achievements from the perspective of complex network or the identification of the key nodes in research achievements transformation, though with quite a few works about the influencing factors of the transformation efficiency of research achievements. Here, we defined a new multiplication to couple the multilayer network, based on the layers and the relationship between the layer n and layer $(n - 1)$. In this way, we get a new adjacency matrix for the multilayer network. With the help of the k -core, we find the vital nodes identification of social network. In Section 3, the simulation network and the real network were tested in this paper. Simulation results indicate that our coupling method can find vital nodes in the multilayer network.

2. Proposed Method

2.1. Multilayer Network Coupling. Multilayer networks pay more attention to the heterogeneity in complex systems, which include the characterization of interaction patterns between different types of nodes and nodes belonging to different network layers. Therefore, the multilayer network research framework is able to describe the structure of complex systems more comprehensively and completely. The nodes and their interaction relationships in a single network can be completely characterized by the adjacency matrix, with which the modeling scheme can be naturally extended to multilayer networks. The matrix representing the multilayer networks is also called the super adjacency matrix or block matrix [23].

An illustrative example of the multilayer network is presented in Figure 1 which consists of three layers, while the node sets for different layers are the same.

The interlayer relationships of the network are built and displayed in Figure 2, where the nodes with the same color are at the same layer while the nodes with different colors are at different layers. If there are connecting lines between nodes in the same layer, or if there are connecting lines between nodes in one layer and connecting lines between

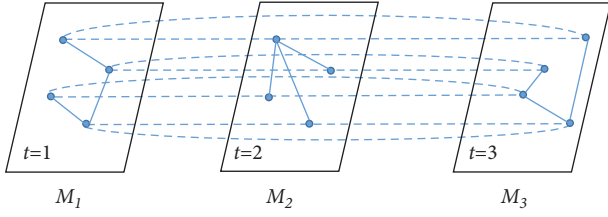


FIGURE 1: The innovation value transformation network.

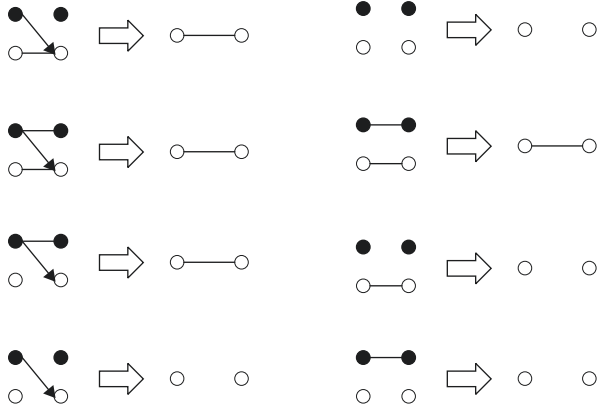


FIGURE 2: Diagram of the network coupling.

another layer and a node in this layer, the nodes of the two layers can be coupled. Otherwise, the coupling cannot be carried out. Specific coupling steps are given in Algorithms 1 and 2.

2.2. K-Coreness (Identification of Key Nodes). A K-core decomposition iteration [24] is carried out to delete nodes and edges with degrees less than k to acquire a subgraph k -core with the degree of each node equal to or greater than k . When a node in a graph exists in the k -core but does not exist in the $k+1$ -core of the graph, the k -core value of this node is k . K-core decomposition determines the k -core value of each node in the social network with specific steps shown in Figure 3. (1) Assume that the degree of each node in the social network is greater than or equal to 1, then the whole network graph is the 1-core G_1 of G ; (2) iteratively delete the nodes with degrees less than 2 from G_1 to acquire a subgraph G_2 , which is the 2-core of G . The k -core value of the deleted nodes is 1 because they exist in the 1-core but do not exist in the 2-core; (3) iteratively delete the nodes with degrees less than 3 from G_2 to acquire a subgraph G_3 , which is the 3-core of G . The k -core value of the deleted nodes is 2 because they exist in the 2-core but do not exist in the 3-core; (4) continue with the step to acquire the k -core value of all nodes in the network.

3. The Method of Constructing Network of Input, Output, and Product

This paper studies the transformation efficiency of scientific research achievements with the samples of annual data of 30 provinces in China (excluding Tibet, Hong Kong,

Macao, and Taiwan) from 1998 to 2016. The raw data are mainly obtained from China's science and technology statistical yearbook, China's high technology statistical yearbook, and China's statistical yearbook over the years. In the knowledge development stage, the internal expenditure of annual R&D funds of each province is selected as the initial input of the innovation value chain, while the number of papers that can be retrieved from the three main thesis retrieval websites and the patent authorization of each province are determined as the output of this stage. In the achievement transformation stage, the new product sales revenue in high-tech industries of each province is selected as the output index. In the industrialization stage, the proportion of high-tech output values in the total industrial output values of each province is taken as the output index.

In this paper, the time series visualization method proposed by Lacasa [25] is adopted to construct the network. The network is constructed for each subsystem of the value transformation system. Firstly, the discrete time series data of a subsystem $x(t)$ is correspondingly regarded as the nodes of the network. According to visual criteria, a connection edge can be built if it is visible between any two data (t^a, x^a) and (t^c, x^c) in $x(t)$. For any point (t^b, x^b) between (t^a, x^a) and (t^c, x^c) , if $t^a < t^b < t^c$, it meets

$$x^b < x^a + (x^c - x^a) \frac{t^a - t^b}{t^c - t^a}. \quad (1)$$

The height of the straight bar in Figure 4(a) corresponds to the data value at each time point. If the top of two straight bars are visible to each other, the corresponding two points are connected in the network in Figure 4(b).

After that, according to the visibility graph, an adjacent matrix of time series can be built. Finally, the network similarity is calculated according to the cosine similarity theorem [26], as presented in Figure 5.

Let the adjacency matrix of a time series network of $x(t)$ at a certain time l be A ; the adjacency matrix of a time series network of $y(t)$ at time m be B ; $A, B \in R_{l \times l}$ where $R_{l \times l}$ is a 0-1 matrix. Then, the cosine value of the included angle of the space vectors $a = (A(:, 1), A(:, 2), \dots, A(:, l))$ and $b = (B(:, 1 + \tau), B(:, 2 + \tau), \dots, B(:, l + \tau))$ reflects the similarity of the two structures.

$$s = \cos \theta = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}| |\vec{b}|} = \frac{\sum_{i=1}^{l^2} a_i \cdot b_i}{\sqrt{\sum_{i=1}^{l^2} (a_i)^2} \cdot \sqrt{\sum_{i=1}^{n^2} (b_i)^2}}. \quad (2)$$

Herein, s represents the similarity and θ denotes the included angle of the two space vectors. As displayed in Figure 6, when the two vectors completely coincide, i.e., $\theta=0$ and $s=1$, then the matrices A and B are exactly the same while the two processes are synchronized in this time period; when the two vectors are completely opposite, i.e., $\theta=180^\circ$ and $s=-1$, then $A+B=0$ while the two processes are reverse synchronized in this time period; when the two vectors are perpendicular to each other, i.e., $\theta=90^\circ$ and $s=0$, then the two processes are completely irrelevant in this time period. In this paper, the range of

Input: upper layer adjacency matrix A^1 , sublayer adjacency matrix A^2 , relationship between upper layer and sublayer B^1
Output: coupling adjacency matrix D

- (1) a_{ij}^1 in A^1
- (2) a_{ij}^2 in A^2
- (3) b_{ij}^1 in B^1
- (4) d_{ij} in D
- (5) **if**
- (6) $b_{ij}^1 = 1 (d_{ij} = a_{ij}^1 \cup a_{ij}^2)$
- (7) **else**
- (8) $(d_{ij} = a_{ij}^1 \cap a_{ij}^2)$
- (9) **end**
- (10) D ;

ALGORITHM 1: Multilayer network coupling in two layers.

Input: first layer adjacency matrix A^1 , second adjacency matrix A^2 , ..., the last layer adjacency matrix A^n , relationship between two layers B^1, B^2, \dots, B^{n-1} .

Output: coupling adjacency matrix D

- (1) a_{ij}^1 in A^1
- (2) a_{ij}^2 in A^2
- ...
- (3) a_{ij}^n in A^n
- (4) b_{ij}^1 in B^1
- ...
- b_{ij}^{n-1} in B^{n-1}
- (5) d_{ij}^1 in D^1
- (6) **if**
- (7) $b_{ij}^1 = 1 (d_{ij} = a_{ij}^1 \cup a_{ij}^2)$
- (8) **else**
- (9) $(d_{ij} = a_{ij}^1 \cap a_{ij}^2)$
- (10) **end**
- (11) **for** $i = 2 : n - 1$
- (12) **if**
- (13) $b_{ij}^1 = 1 (d_{ij} = d_{ij}^{i-1} \cup a_{ij}^{i+1})$
- (14) **else**
- (15) $(d_{ij}^i = d_{ij}^{i-1} \cap a_{ij}^{i+1})$
- (16) **end**
- (17) D ;

ALGORITHM 2: Multilayer network coupling in over two layers.

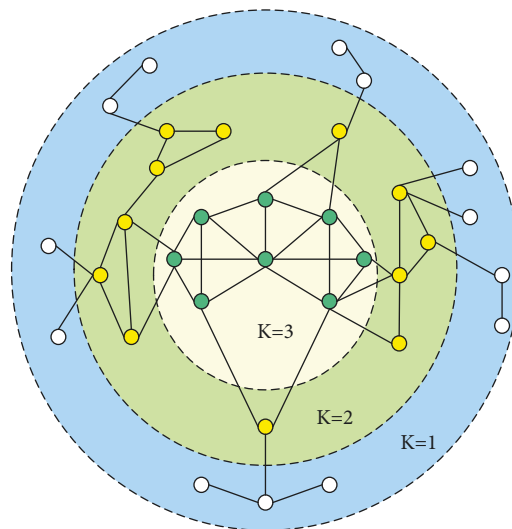


FIGURE 3: Steps to acquire the k -core value of the nodes in the network.

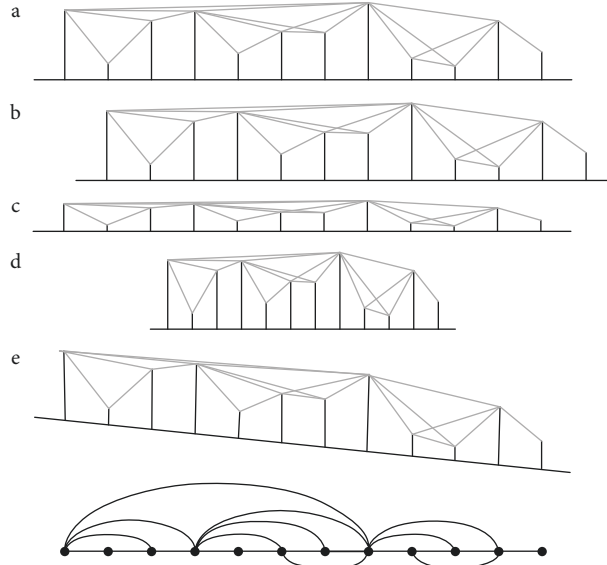


FIGURE 4: Visibility graph theory.

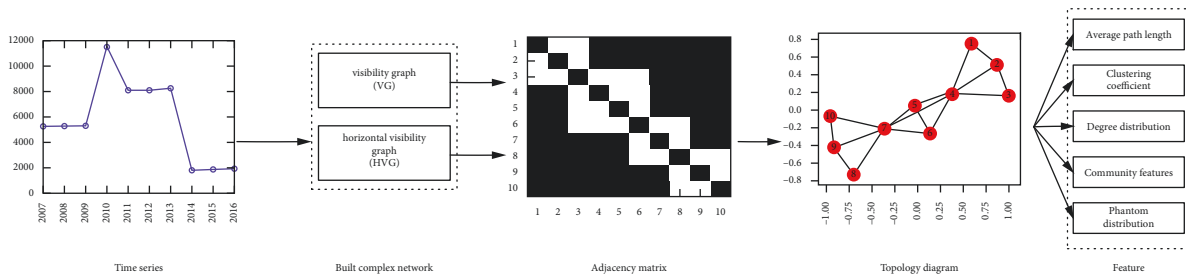


FIGURE 5: Network construction process from time series data.

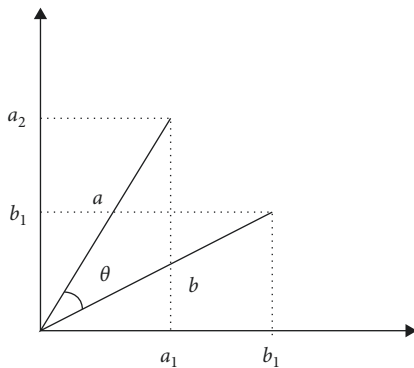


FIGURE 6: Cosine similarity.

similarity $s \in [0, 1]$ as the vectors of the innovation value chain only exists in positive space. Two nodes with a similarity greater than or equal to 0.6 are connected, otherwise not.

4. Result Analysis

The coupling relationship between investment, patent, and product is shown in Figures 7 and 8. In this paper, the multilayer network is coupled into one network to analyze

the research achievement transformation efficiency of 30 provinces with an indicator of k -core. This paper uses MATLAB software and Gephi software to process and analyze the data. As shown in Table 1 and Figure 9, the k -core indicator varies from 2 to 4, where a greater k -core indicates a greater transformation efficiency. Among the 30 provinces, the k -core value of Zhejiang province, Jiangsu province, and Guangdong province is 4, which is the greatest. Furthermore, the k -core value of Fujian Province is 3, while that of the rest of the provinces is 2. Zhejiang province, Jiangsu province, and Guangdong province are located along the coast of China, therefore having superior geographical conditions. With a developed transportation network system, they are important ports for foreign trade which have complete industrial structure and an obvious industrial cluster advantage. For instance, the total output value of the machinery industry in Guangdong province exceeds 500 billion yuan, ranking second among all provinces in China. In addition, these three provinces have a developed education industry. There are many scientific research institutes which cultivate talents with strong scientific and technological innovation ability. For these three provinces, decent communication channels between the supply side and the demand side of research achievements make the transformation more effective. For the rest of the

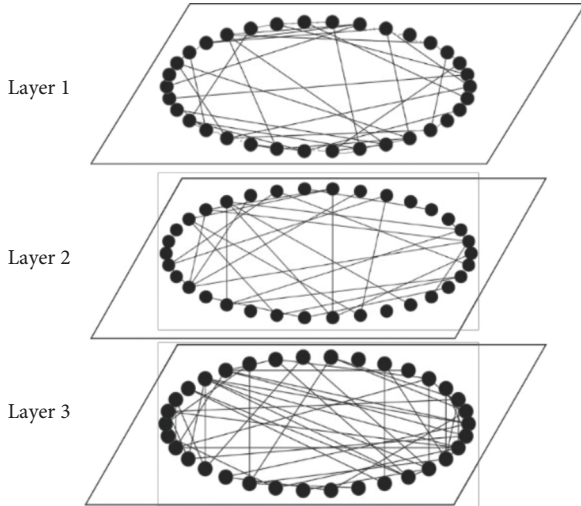


FIGURE 7: The innovation value transformation network: the first layer is the investment network, the second layer is the patent network, and the third layer is the production network.

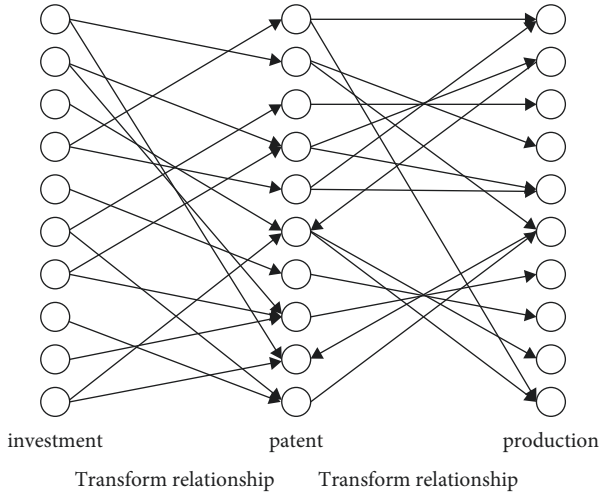


FIGURE 8: The transform from layer 1 to layer 2 and layer 2 to layer 3: the transform of investment to patent as shown in the between investment and patent; the transform of patent to production as shown in the between patent and production.

TABLE 1: The k -core of each node of coupling four layers.

Province	k -core	Province	k -core
Beijing	2	Henan	2
Tianjin	2	Hubei	2
Hebei	2	Hunan	2
Shanxi	2	Guangdong	4
Neimenggu	2	Guangxi	2
Liaoning	2	Hainan	2
Jilin	2	Chongqing	2
Heilongjiang	2	Sichuan	2
Shanghai	2	Guizhou	2
Jiangsu	4	Yunan	2
Zhejiang	4	Xizang	2
Anhui	2	Shaanxi	2
Fujian	3	Gansu	2
Jiangxi	2	Qinghai	2
Shandong	2	Ningxia	2

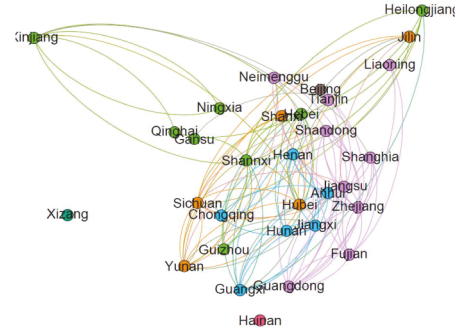


FIGURE 9: The network of coupling three layers and the node.

provinces, the influencing factors of insufficient transformation efficiency lie in the following: (1) imperfect transportation. For example, the lack of ports in inland provinces has become a bottleneck restricting industrial agglomeration; (2) a weak education industry, which leads to a weak strength of the supply side of scientific and technological achievements; (3) brain drain, which is urgently to be solved to retain high-quality talents; and (4) insufficient channels for the transformation of innovative achievements, which requires the corresponding policies and regulations which encourage the transformation and implementation of innovation achievements issued by the government.

5. Conclusions

5.1. Research Conclusions. This paper deals with the transformation efficiency of research achievements. Firstly, the relationships between the transformation efficiency of research achievements and time series vectors are built to construct the subsystem network. Next, the similarity of transformation efficiency over time is calculated based on the cosine similarity theorem. The optimal mapping relationship is solved to determine the transformation effect. On this basis, a multilayer network adjacency matrix is constructed and the key nodes of the network are identified using k -core. Finally, an empirical study was carried out based on the data from China's provincial innovation value transformation system from 1998 to 2016. The transformation efficiency of 30 provinces is calculated and analyzed. Results indicate that (1) the transformation efficiency of value transformation systems is related to the time series network structure of input-output vectors; (2) the similarity of time series networks can reflect the mapping relationships of value transformation parameter vectors, while k -core value can represent the degree of value transformation; and (3) the transformation efficiency of research achievements of different provinces in China is different, where that of coastal provinces is higher.

5.2. Distributions. On the theoretical side, a complete analysis framework of the transformation efficiency of research achievements is constructed. The mapping relationship between the parameter vector of the research innovation achievements transformation system and the time series network structure is demonstrated. The model

and calculation method of transformation efficiency are built while the key nodes of the network are identified. From the perspective of time network, this paper analyzes the research ideas and practical approaches of transformation efficiency. This paper enriches the application research system of complex networks.

On the practical side, the transformation efficiency can be measured, evaluated, and observed. A calculation method as well as a promotion direction of transformation efficiency is proposed.

5.3. Strategy and Advices. To improve the transformation efficiency of research achievements, each province could clarify the development direction according to its own conditions, make centralized breakthroughs in key industries, and form industrial agglomeration effects, according to the empirical analysis results of the transformation efficiency of research achievements. By strengthening the industry-academia-research combination and promoting the connection between the subjects in each stage of the innovative value, a good communication channel could be built and the transformation efficiency could be improved.

However, the external factors such as the environment, economy, and policy which influence the transformation efficiency of research achievements, as well as the relationships and constraints among various research achievements, are not considered in this paper. These relevant contents will be studied in future research to further improve the scientificity and accuracy of the research on the transformation efficiency of research achievements.

Data Availability

The raw data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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