Renewable and Sustainable Energy Reviews 26 (2013) 492–505

Contents lists available at SciVerse ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Patent citation network analysis for the domain of organic photovoltaic cells: Country, institution, and technology field

Hochull Choe [a,b], Duk Hee Lee [b,*], Il Won Seo [b], Hee Dae Kim [c]

[a] Policy Development Team, Strategy and Cooperation Division, Korea Research Institute of Chemical Technology, 141 Gajeongro, Yuseong, Daejeon, 305-343, Republic of Korea
[b] Department of Management Science, KAIST, 335 Gwahakro, Yuseong, Daejeon 305-701, Republic of Korea
[c] Future Strategy Team, Daegu Digital Industry Promotion Agency, 2139-12, Nam-gu, Daegu, 705-701, Republic of Korea

A R T I C L E I N F O

Article history:
Received 1 May 2012
Received in revised form
18 May 2013
Accepted 20 May 2013
Available online 4 July 2013

Keywords:
Patent citation network
Social network analysis
Node centrality
Organic photovoltaic cell

A B S T R A C T

The goal of this work is to understand the structure and characteristics of technological knowledge flows between countries, institutions, and technology fields in the field of organic photovoltaic cells. This study was conducted in three stages: data collection, network creation, and network analysis. For network analysis, network visualization, network topological analysis, and node centrality analysis were performed in sequence. The network topological analysis revealed that all three citation networks, i.e., countries, institutions, and technology fields, are scale-free networks that follow the power law and display, to a greater or lesser extent, a more efficient knowledge transfer capability than a random network of the same size. The node centrality analysis showed that the United States, Japan, and Germany are the most important citation centers in the country citation network, while Boeing, Konarka Technologies, Eastman Kodak, and Sharp are the most important in the institution citation network, and the U.S. patent classification (USPC) classes of 136, 257, and 428 are the most important in the technology field citation network, each playing critical roles in each the network as core nodes. In this study, we applied various concepts of centrality to the analysis of individual nodes and found that the results from the network topological analysis and the node centrality analysis are not significantly different. The proposed analysis framework in this paper is applicable to different science and technology domains.

Contents

Abbreviations: EPFL, École Polytechnique Fédérale de Lausanne; GHG, Greenhouse gas; USPC, U.S. patent classification; USPTO, U.S. Patent and Trademark Office; SET-Plan, the Strategic Energy Technology Plan; TOE, Ton of Oil Equivalent.

* Corresponding author. Tel.: +82 42 350 6306; fax: +82 42 350 6831.
E-mail addresses: dhlnexys@kaist.ac.kr, hchull@gmail.com (D.H. Lee).

1364-0321/$ - see front matter
http://dx.doi.org/10.1016/j.rser.2013.05.037

1. Introduction

Since the 19th century, mankind has depended mostly on fossil fuels for energy needs. However, as the awareness of environmental problems, such as the depletion of fossil fuels and global warming caused by rising levels of GHGs, has increased, the development and security of environmentally-friendly and sustainable energy sources has emerged as a major concern for the global community. In 2006, the U.S. announced its “Advanced Energy Initiative” and outlined a challenging goal to reduce oil imports from the Middle East by 75% by the year 2025 by developing new and renewable energy resources [1]. The EU adopted the “SET-Plan” and set the target of reducing EU emissions of GHGs by at least 20% by 2020, relative to the emissions levels in 1990 [2]. The Korean Government established “The 2nd National Plan for Energy Technology Development” to improve its global competitiveness in energy technology and the industrial sector. This plan aims to develop new and renewable energy technologies and to improve power efficiency by doubling the country's energy-related research and development (R&D) investments by 2020. Additionally, Japan, China and Canada also have set national agendas for the development of new and renewable energy technologies to reduce their dependency on fossil fuels and to foster a strategic green growth industry.

New and renewable energy technologies cover various fields, such as solar thermal, photovoltaics, wind, geothermal heat, and fuel cells. Among these, solar energy, which includes solar thermal and photovoltaics, is sometimes considered the perfect alternative to fossil fuels because it is an inexhaustible source of energy and does not produce GHGs or other pollutants [3]. Accordingly, many countries are promoting the national importance of R&D in solar energy as a key aspect of the new and renewable energy sector.

As mentioned earlier, solar energy is divided largely into two categories, photovoltaics and solar thermal. The former is a method of generating electrical power by the conversion of solar radiation into electricity through the use of photovoltaic cells made of semiconductors. The latter absorbs solar radiation, converts it into heat, and then utilizes the stored heat for cooling, heating, or power generation. Although photovoltaic energy production varies by country, it is generally a significantly larger component of the solar energy industry in comparison to solar thermal energy.[1]

The core technology of photovoltaics is the photovoltaic cell, which is a device that converts light energy into electrical energy. Among the various photovoltaic cells, organic photovoltaic cells have drawn significant attention as an eco-friendly energy source for the future, incorporating active R&D and knowledge transfer activities. The purpose of this paper is to understand the structure and characteristics of the technological knowledge flows between countries, institutions and technology fields by using a patent citation network in the field of organic photovoltaic cells.

[1] The annual growth rates in the supply of the new and renewable energy sector in OECD countries from 1995 to 2007 shows that photovoltaic energy exhibited the highest growth rate (43.2%), while solar thermal energy remained at 6.8% [4]. In Korea, compared with 30,700 TOE of solar thermal energy supply in 2009, the supply of photovoltaic energy reached 121,700 TOE, which is almost four times higher [5]. In the U.S., photovoltaic energy occupies the largest proportion in the solar energy industry [1], and the Solar Energy Program initiated by the U.S. federal government places the highest priority on the photovoltaic energy market [6].

2. Literature Review

The citation information contained in both scientific publications and patents has been the most important and basic indicator by which to measure the impact of such publications and patents [7]. Patent citations, in particular, are widely believed to represent knowledge transfer or knowledge spillover [8] and have been much used to measure disembodied knowledge flows between industries or technology fields [9].

However, there are a few drawbacks to the use of patent data as an indicator of technological knowledge flow. The first drawback involves whether patents can be used to represent technological knowledge. This arises from the fact that not all inventions are patented and patentable [10,11]. In reality, only some inventions are patented [12], and not all patents become innovations [10]. The second drawback is that the propensity to patent varies across technology sectors [10,13]. Patent protection is less significant in some industries [14]. Other means of protection, such as trade secrets or trademarks, might be preferred by individual firms to protect their technological know-how [15]. This propensity can cause bias in the analysis of technological knowledge flow when using patent data. Third, the inventive quality of patents varies greatly. That is, not all patents have equal value [16]. Few patents actually possess high technological and economic value. These three aspects may decrease the significance and value of patent data.

Despite these limitations to patent data, many attempts have been made to date to analyze knowledge flows using patent data. It is because the value of a patent is generally proportional to the citation count number [17,18]; additionally, patent citations can provide information on the diffusion of technologies in a certain technology domain [19]. From the viewpoint of technological knowledge flows, patents, as a medium for the disclosure of technology, clearly show the developmental trace of the technology because they contain the “prior art” [19]. Additionally, patent citations provide good evidence of the links between technological antecedents and descendants [20]. Therefore, patent citations have become one of the main indicators used to explain technological relationships.

In this sense, patents and patent citations are typically considered to be very useful in the study of technological knowledge flows, as has already been demonstrated in previous studies. Huang et al. [21] analyzed patent citation networks in the field of nanoscale science and engineering, presenting the longitudinal changes in R&D in this technology field. Hu and Jaffe [22] used patent citation information to examine the patterns of knowledge diffusion between countries. Kajikawa and Takeda [23] studied the literature citation network of organic light-emitting diodes (OLED) to investigate the structure of research and to detect emerging research domains. No et al. [20] attempted to deepen the understanding of technological trajectories and trends by utilizing patent citations in nanobiotechnology fields. Yoon et al. [24] constructed a patent network based on semantic patent analysis, identifying the

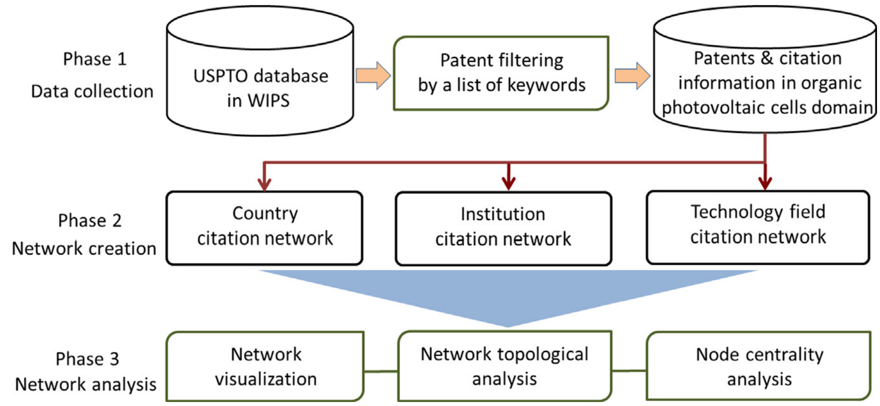

Fig. 1. The research framework of patent citation networks.

technological trends. Moreover, Lai and Wu [25] proposed a new approach to patent classification for better technology positioning and forecasting by using patent co-citation analysis of bibliometrics.

The greatest advantage of patent data is that they represent a direct outcome of the invention process [26,27]. By considering the fact that inventions are the source of new technological knowledge, even if not all inventions can be patented, it is obvious that patent data represent some of the most significant indicators of technological knowledge and innovation.

Patent citation analysis begins with an examination of the citation relationship between different patents or between patents and the scientific literature [28].[2] The statistical analysis of patents and patent citations is a conventional research method, used to observe or measure technological knowledge flows [29]. However, such a method can only inform us with partial characteristics of the knowledge flow [30], which poses a limitation; hence, an approach that incorporates patent citation information with social network theory has been developed. Social network analysis is a quantitative technique based on graph theory. It is used to understand the interactions among actors (nodes). Social network methods are continuously evolving, although network topological analysis and node centrality analysis are commonly used.

The network topological analysis of either scientific literature or patent citations is helpful in widening our understanding of the structure of the citation network and provides a holistic perspective of knowledge flow. Previous studies on the citation network found that the network has the characteristics of a scale-free network with a power-law degree distribution. Bilke and Peterson [31] confirmed that the citation network in high energy physics publications is a scale-free network with a power-law distribution. Chen and Hicks [7] analyzed the link between science and technology by using the paper-patent citations in the field of tissue engineering and found that a power-law degree distribution phenomenon exists within that citation network. Okamura and Vonortas [32] analyzed patent citations in five industrial sectors and verified that their degree distribution follows a power law. Li et al. [30] studied nanotechnology patents and their citations and found that the corresponding patent document citation network follows the scale-free model. Hung and Wang [33] identified that the patent citation network roughly follows a power-law distribution by analyzing patents in the field of radio frequency identification (RFID).

Network topological analysis is very useful in understanding the overall flow of technological knowledge by providing information on the network structure, but it cannot provide quantitative information on the importance and value of individual nodes. This paper makes more progress in identifying the importance and value of individual nodes, presenting a centrality analysis that can be a useful method for the measurement of the structural location of an individual node and for assessing its importance. Centrality is an index representing the extent to which a node is located at the center of the entire network. Because the actual value and importance that “a center” has within one network has been proved [34–37], we can identify the value and importance of an individual node by using the concept of centrality. There exist various methods to measure the centrality of a node, each of which has its own unique characteristics. This study analyzes individual nodes by using the three types of centrality suggested by Freeman [38].

We first review the structure and characteristics of the patent citation network for each analytical unit of country, institution and technology field through the use of network visualization and network topological analysis. Then, we identify the value and importance of an individual node by using centrality analysis.

3. Research Design

Organic photovoltaic cells have drawn significant attention as a new energy source for the future because they are more flexible, cheaper, and more eco-friendly than other photovoltaic cells. Patent applications and registrations in the field of organic photovoltaic cells have increased rapidly since 2001, and as a result, the corresponding knowledge flow has changed dynamically. Therefore, the field of organic photovoltaic cells is well merited for studying the structure and characteristics of technological knowledge flows.

This paper presents the results of network visualization, network topological analysis, and node centrality analysis in understanding the technological knowledge flows of patent citation networks in the field of organic photovoltaic cells. The reported results cover three analytical units. The research framework of this study is presented in Fig. 1.

3.1. Analytical units

Because a patent can be both easily accessed in electronic form and easily categorized according to various criteria, such as the technology, inventor or assignee [39,40], its analytical units are vary significantly. The most familiar analytical units of a patent are the patent document, assignee, assignee country, and technology field; additionally the inventor and industry also can be used as the analytical units. With respect to a patent citation network, the analytical units are regarded as nodes, while citing and the cited

[2] This paper does not examine the citation relationship between a patent and a scientific publication but limits the scope of study to the analysis of the citation relationship between patents.

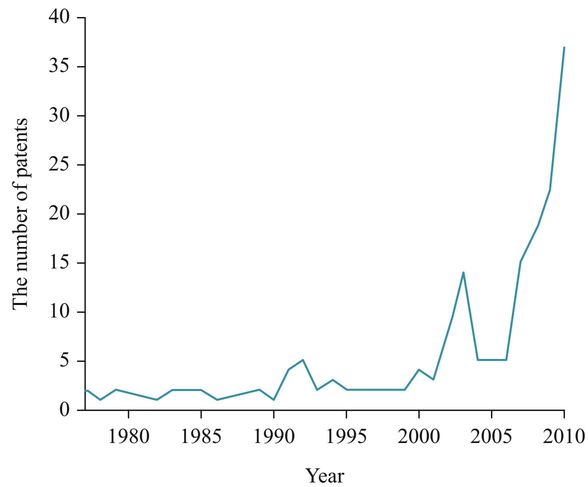

Fig. 2. The registered patents in the organic photovoltaic cells domain.

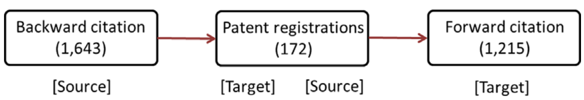

Fig. 3. The backward and forward citations of registered patents in the organic photovoltaic cells domain.

relationships between such analytical units are called links. Thus, a patent citation network is a directed network and can be, according to the analytical units, constructed in various forms, including the patent document citation network, the patent assignee country citation network, the patent assignee institution citation network, the patent technology field citation network, or the patent industry citation network, among others. Because the analytical units in this paper are country, institution, and technology field, we establish the patent assignee country citation network, the patent assignee institution citation network, and the patent technology field citation network.

3.2. Network analysis

3.2.1. Network visualization and network topological analysis

We first visualize a network map to assess a general overall structure of the network. Then, we analyze the structural and topological characteristics of the network by using various statistical indices, as suggested by Albert and Barabasi [40], and compare these results with those from a random network of the same size.

- The number of nodes and links: These are basic indices that indicate the size of a network.
- Density: This is defined as the ratio of actual links to all possible links in the network. Generally, as a network grows in size, the density decreases.
- Average degree: The degree is defined as the number of links that a given node has to other nodes. Thus, the average degree is calculated by dividing the sum of all node degrees by the total number of nodes in the network.
- Average path length: This is the average value of the geodesic path length between any pair of nodes in the network. As the average path length decreases, technology and information diffuse faster through the network.
- Diameter: This is the length of the largest geodesic path in the network.
- Number of components: A component is an isolated subnetwork in the network. There are no conditions for becoming a component unless disconnection between nodes occurs. The number of components indicates the number of independent groups in the network.
- Clustering coefficient: A node's clustering coefficient is the ratio of the number of actual links between the node's neighbors to the maximum possible number of links between those neighbors. The network's clustering coefficient is the average of the clustering coefficients for all of the nodes. It indicates the degree to which nodes in the network tend to cluster together.
- Centralization index: This indicates the extent to which a network is concentrated in the center. The centralization analysis suggests whether the network has a centralized structure or not [41]. This study uses the degree centralization to calculate the centralization index. The degree centralization is calculated by finding the total sum of values gained by subtracting the degree centrality[3] of each node from the maximum degree centrality within the network, followed by dividing the total sum by the theoretically possible maximum of degree centrality.[4]
- Power-law degree distribution: This indicates that a relationship between the degree distribution (Y) and a node's rank on the degree (X) in the network follows the function of $Y=aX^{-b}$.[5] Normally, a graph is used to determine whether the data follow a power law. When $\log(Y)=\log(a)-b\log(X)$, which is a converted form of the function above in which the logs of both sides are taken, leading to a linear plot, it is assumed to be under the power law. However, this visual approach is vague and more likely to lead to an error. Recently, a goodness-of-fit test for a power-law degree distribution based on the Kolomogorov–Smirnov (KS) statistic was proposed [42]. If the p-value of the goodness-of-fit test is large (close to 1), then our dataset fits the power-law distribution. If the p-value of the goodness-of-fit test is smaller than 0.1, then the dataset does not fit the power-law model.[6]

3.2.2. Critical node analysis using the node centrality

Following the structural and topological analysis of the whole network, the centrality analysis is performed to examine the importance and value of each node. The centrality is an actor-related variable at the individual level but can be calculated under consideration of the whole network [43]. We conduct the hub, authority and broker analysis by using degree centrality, clos eness centrality, and betweenness centrality, as suggested by Freeman [38].

3.2.2.1. Hub and authority analysis. The patent citation network is a directed network. The direction of a link is determined by the citation relationship, i.e., citing or cited. Thus, two separate degrees are defined, the in-degree and out-degree. The in-degree represents the number of times a node cites other nodes. The out-degree represents the number of times a node is cited by other nodes.

Hubs and authorities in the citation network are identified based on node degree. The former is related to the in-degree, and the latter is related to the out-degree. In other words, a hub is a node that cites many other nodes, and an authority is a node that is cited by many other nodes [30]. Instead of using the node

[3] For details on the degree centrality, see Eq. (1).

[4] The theoretically possible highest degree centrality appears in a star network. The star network is a network in which all nodes are connected to a certain node, but the rest of nodes are not linked to each other. Thus, let n denote the total number of nodes in the network, then the theoretically possible highest degree centrality is (n-1)(n-2).

[5] In the equation of $Y=aX^{-b}$, b is called "power-law exponent."

[6] For details on the test and p-value, refer to [42].

degree, we analyze hub and authority by using two types of centrality, which adopt the concept of node degree for calculation.

- Local hub and authority: First, we use the degree centrality, which is measured by the degree between a node and its neighbors. Because the degree centrality is measured based on the number of other nodes directly connected to one node, we can deduce the local hub and local authority by using the degree centrality. The degree centrality of Node i ($C_d(i)$) is calculated by the following equation [38]:

$$C_d(i) = [\Sigma_{k=1}^{n} a(N_i, N_k)]/(n-1) \quad (1)$$

where $a(N_i, N_k)$ is 1, if and only if Node i (N_i) and Node k (N_k) are connected by a line; otherwise it is 0. n is the number of nodes in the network; therefore, $(n-1)$ is the theoretical maximum degree of a node in the network.
According to Eq. (1), because the degree centrality calculation is limited by the number of nodes that are directly connected to a node, indirectly connected nodes that are more than two steps apart are not included for the measurement. The degree is measured only within the local range in which the node has a direct link, so the degree centrality has the meaning of local centrality. Thus, we can determine a local hub by using in-degree centrality and a local authority by using out-degree centrality.
- Global hub and authority: We use closeness centrality for global hub and authority analysis. The closeness centrality is an index representing the degree to which a node is located to the center. Thus, we can determine the global hub and authority by using the closeness centrality. The shortest path from every node to every other node is used for calculating the closeness centrality. The closeness centrality of Node i ($C_c(i)$) is calculated by the following equation [38]:

$$C_c(i) = (n-1)/[\Sigma_{k=1}^{n} d(N_i, N_k)] \quad (2)$$

where $d(N_i, N_k)$ is the number of links in the geodesic linking Node i (N_i) and Node k (N_k), and n is the number of nodes in the network. Therefore, $(n-1)$ is the minimum sum of distances for a node that is adjacent to all other nodes.
As can be seen from Eq. (2), unlike the degree centrality, the closeness centrality is calculated by using both the direct and indirect links; hence, the global centrality of a node can be measured by the closeness centrality. That is, increasing closeness centrality indicates the decreasing distance between a given node and the other nodes. We can identify a global hub by using in-closeness centrality and a global authority by using out-closeness centrality.

3.2.2.2. Broker (gatekeeper) analysis. To measure the degree to which a node plays the role of an intermediary or bridge between the nodes in a network, betweenness centrality analysis is performed. The betweenness centrality is an index that indicates the degree to which a node is located in the shortest path between other nodes. A node with high betweenness centrality is called a broker or a gatekeeper [44]. Nodes with high betweenness centrality play the role of bridging the flow and change of information between other nodes throughout the whole network. Thus, a node with higher betweenness centrality has greater control of the information that it gains, and the more dependent other nodes become on that node. The betweenness centrality of node i that is located between node j and node k is calculated as a ratio of the shortest paths connecting j and k that also include i in the network. The betweenness centrality of Node i ($C_b(i)$) is calculated by the following equation [38]:

$$C_b(i) = [\Sigma_{j=1} g_{jk}(i)/g_{jk}]/[(n-2)(n-1)/2] \quad (3)$$

where g_{jk} is the number of geodesics linking Node j and Node k; $g_{jk}(i)$ is the number of geodesics linking Node j and Node k ($j \neq k$) that contain Node i; and $(n-2)(n-1)/2$ is the maximum value taken by $\Sigma_{j=1} g_{jk}(i)/g_{jk}$, achieved only by the central point in a star [45].

4. Data collection and network creation

This paper uses the online patent search service WIPS (wips.co.kr) to construct a patent citation network in the field of organic photovoltaic cells. WIPS provides patent data, which has been collected from patent offices in Korea, the U.S., EU, China, and Japan. For analysis, this study selected only the limited number of patents currently registered in the USPTO[7] (Figs. 2 and 3).

To extract the relevant patents in the field of organic photovoltaic cells, we searched with a list of keywords in the title, abstract and exemplary claim. The search was carried out on July 14, 2011, and showed that a total of 172 patents were registered between February 22, 1977, when the first patent was filed, and December 31, 2010. From a periodical perspective, from 1977 to 2000, less than five patents were registered each year, but after 2001, the number of patent registrations increased rapidly. In 2010, 37 patents were registered. Among the 172 patents filed, 132 patents comprising 77% of the total were registered after 2001.

To construct the patent citation network, we analyzed the citation information displayed in the 172 registered patents, extracting 1,643 backward citations and 1,215 forward citations. Because the total number of registered patents in the field of organic photovoltaic cells is 172, one registered patent has, on average, 9.6 backward citations and 7.1 forward citations.

We constructed three patent citation networks for different analytical units using a total of 2,858 elements of patent citation information.

- The country citation network: This is the patent assignee country citation network. In the country citation network, a node is a country, and a link is a citing/cited relationship between patents belonging to different countries.
- The institution citation network: This is the patent assignee institution citation network. In the institution citation network, a node is an institution, and a link is a citing/cited relationship between patents belonging to different institutions.
- The technology field citation network: To construct the technology field citation network, we used the USPC. The USPC uses approximately 450 classes and 150,000 sub-classes to categorize patents [46]. We built up the network based on classes. In the technology field citation network, a node is a technology field, namely, classes in the USPC, and a link is a citing/cited relationship between patents belonging to different technology fields.

5. Network Analysis

5.1. Country citation network

5.1.1. Network visualization and the network topological analysis results

The organic photovoltaic cells country citation network between 1977 and 2010 is composed of 27 countries and 114 inter-country citation relations. The network is shown in Fig. 4.

[7] Because many assignees tend to apply for a patent with their national intellectual property office and the USPTO at the same time, the USPTO database is the most representative and reliable [22].

This figure shows the whole network of country citations. The following results were found.

- The U.S. is the most important node in the country citation network. U.S. patents actively interact with the patents of most other countries, especially the patents of Japan (JP) and Germany (DE).
- JP and DE form a secondary citation group.
- S. Korea (KR), Taiwan (TW), Great Britain (GB), and Switzerland (CH) form a third citation group.
- A significant number of interactions are between the U.S., JP, and DE.
- Belgium (BE), Malaysia (MY), New Zealand (NZ), and Denmark (DK) only interact with the U.S.

The network topological measures of the country citation network are shown in Table 1. In the network, the density is 0.148, and the average degree of each node is 3.852. These measures are slightly lower than those of a random network of the same size.

The country citation network also has a small average path length (1.932) and a small diameter (4). These values are slightly smaller than the average path length and diameter of a random network of the same size. The average path length and diameter are indices that indicate the number of links necessary to disseminate knowledge from one country to another. Thus, having a smaller average path length and diameter means that the process of knowledge diffusion within the country citation network is slightly more efficient than in a randomly-connected network. The average path length also suggests that nodes in the country citation network are connected to each other through two steps, on average.

The country citation network has only one component, which indicates that no isolated nodes exist in the network. In other words, all countries in the country citation network are directly or indirectly connected, and from the perspective of technological knowledge flow, each country influences or is influenced by every other.

The country citation network has a significantly larger clustering coefficient (0.750) than that of the same-sized random network. This suggests that nodes are more closely connected in the country citation network than in a random network of the same size.

The degree centralization index (in-degree: 0.546, out-degree: 0.712) is significantly higher than in a random network of the same size. This means that network centralization for a node with high degree centrality is significantly higher than that of a random network. In particular, the fact that the out-degree centralization index is higher than the in-degree centralization index indicates that the degree to which the network is concentrated to a center is higher in a cited network than in a citing network.

We analyzed whether the distribution of links follows the power law in the country citation network. The *p*-values of both degree distributions are significantly larger than 0.1 (in-degree: 0.72, out-degree: 0.58). These values indicate that the country citation network, unlike the random network, is a scale-free network that follows the power law, where the number of links is unevenly distributed.

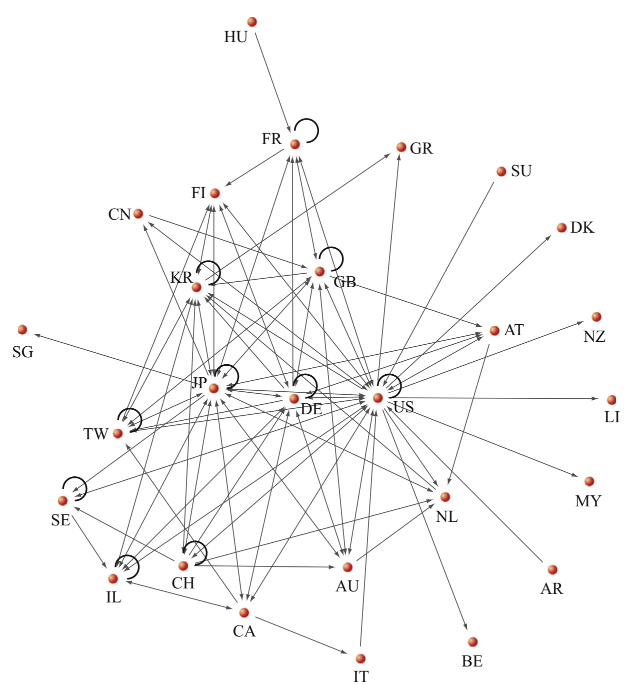

Fig. 4. The country citation network.

5.1.2. *Critical node analysis results*

5.1.2.1. Hub analysis. The hub analysis results for the country citation network are shown in Table 2. The left side of the table indicates the results of local hub analysis by using in-degree centrality, while the results of global hub analysis based on the use of in-closeness centrality are presented on the right side. The two analytical results are very similar, due to the fact that the country citation network is a small network consisting of 27 nodes and 114 links. From the top five hubs, the following results were found.

- The U.S., JP, DE, KR, and TW hubs play key roles in the country citation network. In particular, the U.S., which ranks No. 1 in both in-degree centrality and in-closeness centrality, is the most important hub in the country citation network.
- JP, DE, KR, and TW form a group of secondary patent citation hubs.

5.1.2.2. Authority analysis. The authority analysis results for the country citation network are shown in Table 3. The left side of the

Table 1
The country citation network topological analysis results.

Network	No. of nodes	No. of links	Density	Average degree	Average path length	Diameter	No. of components	Clustering coefficient	Degree centralization	Power-law distribution		
										Power-law exponent (b)	KS statistic	*p*-value
Country citation network	27	114	0.148	3.852	1.932	4	1	0.750	In: 0.546 Out: 0.712	In: 3.072 Out: 2.525	In: 0.076 Out: 0.094	In: 0.72 Out: 0.58
Random network			0.162	4.222	2.309	5	1	0.319	In: 0.115 Out: 0.157	–	–	–

Table 2
The top 5 hubs of the assignee country citation network.

Local hub			Global hub		
Rank	Country	In-degree centrality	Rank	Country	In-closeness centrality
1	United States (US)	0.6538	1	United States (US)	0.6689
2	Japan (JP)	0.4615	2	Japan (JP)	0.5495
3	Germany (DE)	0.3077	3	Germany (DE)	0.4662
4	S. Korea (KR)	0.2692	4	S. Korea (KR), Taiwan (TW)	0.4396
5	Taiwan (TW), Finland (FI), Israel (IL)	0.2308			

Table 3
The top 5 authorities of the assignee country citation network.

Local authority			Global authority		
Rank	Country	Out-degree centrality	Rank	Country	Out-closeness centrality
1	United States (US)	0.8077	1	United States (US)	0.8138
2	Japan (JP)	0.6154	2	Japan (JP)	0.6782
3	Germany (DE)	0.3846	3	Germany (DE)	0.5652
4	Great Britain (GB), Switzerland (CH)	0.2692	4	Great Britain (GB), Switzerland (CH), Canada (CA)	0.5087

table indicates the results of the local authority analysis based on the use of out-degree centrality, while the results of the global authority analysis based on the use of out-closeness centrality are presented on the right side. Similar to the hub analysis, the two analytical results are very similar. From the top five authorities, the following results were obtained.

- The U.S., JP, DE, GB, and CH authorities play key roles in the country citation network. In particular, the U.S., which ranks No. 1 in both out-degree centrality and out-closeness centrality, is the most important authority in the country citation network.
- JP, DE, GB, and CH form a group of secondary patent citation authorities.

5.1.2.3. Broker analysis. The broker analysis results for the country citation network are shown in Table 4. From the top five brokers, the following results were obtained.

- The results of the betweenness centrality analysis show that the U. S. is the most important broker, which means that the U.S. plays a key role in bridging the flow of technological knowledge between many of the countries in the country citation network.
- After the U.S., JP is an important broker.
- Following the U.S. and JP, Canada (CA), GB, and France (FR) play the next most important roles as brokers, in descending order.

5.2. Institution citation network

5.2.1. Network visualization and the network topological analysis results

The institution citation network of the organic photovoltaic cells domain between 1977 and 2010 consists of 518 institutions and 1,115 inter-institution citation relations. The network is shown in Fig. 5. This figure shows the institution citations for which the number of links is more than three. We observed the following results.

Table 4
The top 5 brokers of the assignee country citation network.

Rank	Country	Betweenness centrality
1	United States (US)	0.3934
2	Japan (JP)	0.1234
3	Canada (CA)	0.0615
4	United Kingdom (GB)	0.0387
5	France (FR)	0.0359

- Konarka Technologies is located in the center of the network. The patents owned by Konarka Technologies actively interact with the patents of many other institutions.
- JX Crystals and Universal Display form a local citation cluster.
- Boeing is the only node located between the main cluster headed by Konarka Technologies and the local cluster headed by JX Crystals, playing a broker's role by bridging these two clusters.
- Several nodes connect the main cluster headed by Konarka Technologies with a local cluster headed by Universal Display.

Table 5 shows the network topological measures of the institution citation network. The network has a small average degree (2.066) with rare density (0.004). These measurements are very close to those of a random network of the same size.

The institution citation network has a small average path length (4.070). This figure suggests that the knowledge in one institution can be transferred to others through four steps, on average. The average path length and diameter (9) of the network are significantly smaller than those of the same-sized random network, which indicates that the knowledge diffusion process in the institution citation network is more effective than that in a randomly connected network.

The institution citation network is composed of 6 components (see Table 6). The largest component contains 508 (98.069%) institutions. The high percentage means that most institutions directly or indirectly connect to each other. Therefore, almost all of the institutions can influence or can be influenced by the other institutions in the network.

The institution citation network has a significantly larger clustering coefficient (0.311) than that of a random network of the same size. This high clustering coefficient suggests that institutions have a stronger tendency to gather together according to either their technology fields or interests in the institution citation network in comparison with the random network.

The degree centralization index (in-degree: 0.160, out-degree: 0.085) is higher than that of the same-sized random network. These high figures indicate that network centralization for a node with high degree centrality is significantly higher than that of the same-sized random network.

The degree distribution measures show that the p-value of in-degree distribution is 0.52, while that of the out-degree distribution is 0.71. These results mean that the institution citation network is a scale-free network that follows the power law, where a small number of nodes occupy a large number of links by preferential attachment.

5.2.2. Critical node analysis results

5.2.2.1. Hub analysis. The results of the in-degree centrality and in-closeness centrality analyses for the institution citation network are shown in Table 7. We found the following results.

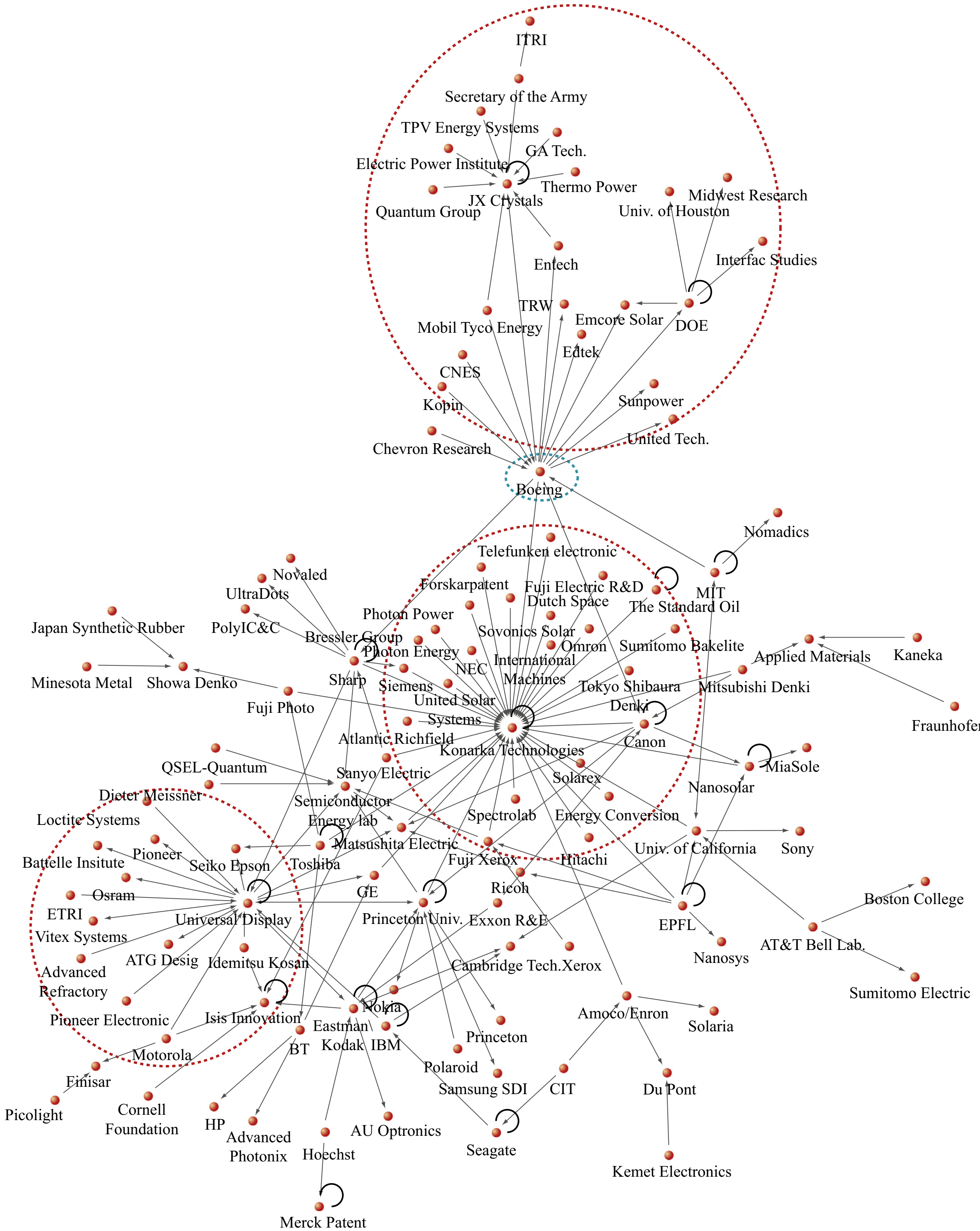

Fig. 5. The institution citation core network.

- Konarka Technologies ranks No. 1 in both in-degree centrality and in-closeness centrality. This means that Konarka Technologies cites patents in the field of organic photovoltaic cells most frequently, whether directly or indirectly. In other words, Konarka Technologies is the most important local and global hub in the institution citation network.
- Sharp also ranks high in both in-degree centrality and in-closeness centrality. Sharp is an important local and global hub

Table 5
The institution citation network topological analysis results.

Network	No. of nodes	No. of links	Density	Average degree	Average path length	Diameter	No. of components	Clustering coefficient	Degree centralization	Power-law distribution		
										Power-law exponent (b)	KS statistic	*p*-value
Institution citation network	518	1115	0.004	2.066	4.070	9	6	0.311	In: 0.160 Out: 0.085	In: 3.232 Out: 2.021	In: 0.075 Out: 0.034	In: 0.52 Out: 0.71
Random network			0.004	2.153	7.079	18	11	0.013	In: 0.011 Out: 0.011	–	–	–

Table 6
The components in the institution citation network.

Component	Size	Percent	Density
1	508	98.069	0.004
2	4	0.772	0.250
3	2	0.386	0.500
4	2	0.386	0.500
5	1	0.193	–
6	1	0.193	–

Table 7
The top 5 hubs of the institution citation network.

Local hub			Global hub		
Rank	Institution	In-degree centrality	Rank	Institution	In-closeness centrality
1	Konarka Technologies	0.0890	1	Konarka Technologies	0.2713
2	JX Crystals	0.0290	2	Eastman Kodak	0.2185
3	Universal Display	0.0232	3	Sharp	0.2143
4	AU Optronics	0.0174	4	Samsung SDI	0.2133
5	Sharp	0.0155	5	Seiko Epson	0.2008

Table 8
The top 5 authorities of the institution citation network.

Local authority			Global authority		
Rank	Institution	Out-degree centrality	Rank	Institution	Out-closeness centrality
1	Boeing	0.0387	1	Boeing, IBM	0.2199
2	Universal Display	0.0329			
3	EPFL	0.0290	3	Sharp	0.1909
4	IBM	0.0213	4	Exxon Research & Engineering	0.1907
5	Sharp, University of California	0.0174	5	Eastman Kodak	0.1896

in the institution citation network, which frequently cites patents in the field of organic photovoltaic cells, whether directly or indirectly.

- JX Crystals, Universal Display and Au Optronics are major local hubs that directly cite patents in the field of organic photovoltaic cells, while Eastman Kodak, Samsung SDI and Seiko Epson are major global hubs that directly or indirectly cite patents in the field of organic photovoltaic cells.

Table 9
The top 5 brokers of the institution citation network.

Rank	Institution	Betweenness centrality
1	Boeing	0.0751
2	Eastman Kodak	0.0682
3	Sharp	0.0668
4	Konarka Technologies	0.0616
5	MIT	0.0526

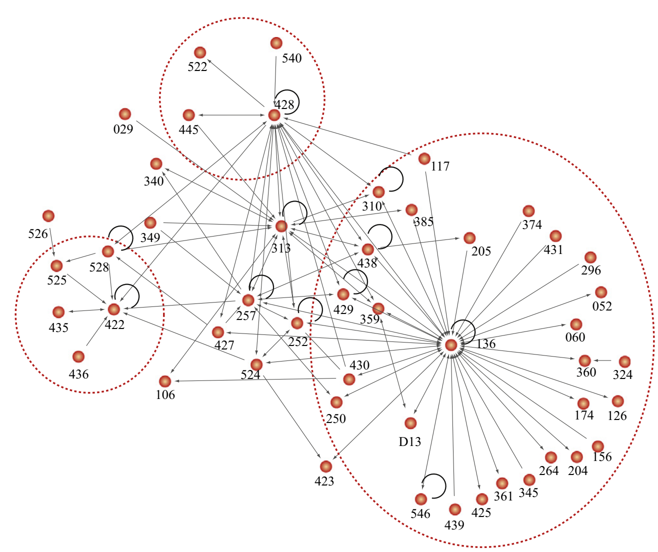

Fig. 6. The technology field citation core network.

5.2.2.2. Authority analysis. The authority analysis results for the institution citation network are shown in Table 8. Our findings are reported as follows.

- The results show that Boeing, IBM and Sharp are important authorities in the institution citation network. Boeing ranks No. 1 in both out-degree centrality and out-closeness centrality. More specifically, Boeing is the most important local and global authority in the institution citation network.
- IBM and Sharp rank 4th and 5th, respectively, in out-degree centrality, while ranking 1st and 3rd in out-closeness centrality. IBM and Sharp also are core local and global authorities in the institution citation network.
- Universal Display, EPFL and University of California are major local authorities, while Exxon Research & Engineering and Eastman Kodak are major global authorities.

5.2.2.3. Broker analysis. We performed a broker analysis of the institution citation network by using the betweenness centrality,

Table 10
The technology field citation network topological analysis results.

Network	No. of nodes	No. of links	Density	Average degree	Average path length	Diameter	No. of components	Clustering coefficient	Degree centralization	Power-law distribution		
										Power-law exponent (b)	KS statistic	*p*-value
Technology field citation network	114	404	0.030	3.377	2.608	7	1	0.716	In: 0.384 Out: 0.429	In: 1.836 Out: 1.595	In: 0.068 Out: 0.080	In: 0.55 Out: 0.32
Random network			0.031	3.544	3.853	8	1	0.054	In: 0.049 Out: 0.040	–	–	–

the results of which are shown in Table 9. Our findings are reported below.

- Boeing ranked No. 1 in the analysis of betweenness centrality and was the most important broker in the institution citation network. As can be seen from Fig. 5, Boeing plays the only role as a bridge connecting the main cluster headed by Konarka Technologies and the local cluster headed by JX Crystals.
- Following Boeing, Eastman Kodak, Sharp, Konarka Technologies and MIT were the next most important brokers in the institution citation network, in descending order.

5.3. *Technology field citation network*

5.3.1. *Network visualization and the network topological analysis results*

The organic photovoltaic cells technology field citation network between 1977 and 2010 is composed of 114 technology fields and 404 inter-technology field citation relations. The network is shown in Fig. 6[8]. This figure shows the technology field citations for which the number of links is more than three. We observed the following results in our analysis.

- The technology field “136 Batteries: thermoelectric and photoelectric” is the largest node in the organic photovoltaic cells domain.
- The technology fields “422 Chemical apparatus and disinfecting, deodorizing, preserving or sterilizing” and “428 Stock material or miscellaneous articles” form a local citation cluster.
- The technology fields “252 Compositions,” “257 Active solid-state devices (e.g., transistors, solid-state diodes),” “313 Electric lamp and discharge devices,” and “438 Semiconductor device manufacturing: process” are closely related to each other.

The network topological measures of the technology field citation network are shown in Table 10. The density (0.030) and average degree (3.377) approximate those of a random network of the same size.

The technology field citation network has a small average path length (2.608) and a small diameter (7) in comparison with those of the same-sized random network. The measurement of the average path length indicates that the knowledge in one technology field can be transferred to others through two or three steps, on average. The smaller average path length and diameter mean that the knowledge transfer process in the technology citation network is faster than that in the random citation network.

The technology field citation network has only one component. This can be interpreted such that, as in the country citation network, all technology fields in the technology field citation network are directly or indirectly connected, and each influences or is influenced by all others.

[8] For the titles of the technology fields incorporated in Fig. 6, see Table A4 in Appendix A.

Table 11
The top 5 hubs of the technology field citation network.

Local hub			Global hub		
Rank	Technology field	In-degree centrality	Rank	Technology field	In-closeness centrality
1	136	0.4071	1	136	0.4838
2	257	0.2566	2	257	0.3941
3	428, 438	0.2301	3	428	0.3889
			4	438	0.3864
5	422	0.2035	5	252	0.3839

Table 12
The top 5 authorities of the technology field citation network.

Local authority			Global authority		
Rank	Technology field	Out-degree centrality	Rank	Technology field	Out-closeness centrality
1	136	0.4513	1	136	0.4921
2	428	0.2301	2	428	0.4306
3	257	0.2124	3	257	0.4116
4	313, 528, 429	0.1416	4	528	0.4040
			5	313	0.3919

The technology field citation network has a significantly higher clustering coefficient (0.716) than that of the same-sized random network. This high measurement indicates that the nodes have closer relationships with each other than those in a randomly connected network.

The degree centralization index (in-degree: 0.384, out-degree: 0.429) is significantly higher than that of a random network of the same size. This means that the degree to which a network is concentrated to the center is significantly higher in the technology field citation network than the random network.

The *p*-values of both degree distributions are shown in the degree distribution measures in Table 10. The values show that the technology field citation network follows the scale-free model, which indicates that a few high degree technology fields exist in the network.

5.3.2. *Critical node analysis results*

5.3.2.1. Hub analysis. The results of the in-degree centrality and in-closeness centrality analyses for the technology field citation network are shown in Table 11. Like the country citation network, both analytical results are very similar, due to the fact that the technology field citation network also is a small-sized network composed of 114 nodes and 404 links. Our analysis suggests the following results.

- 136, 257, 428, and 438 are the core hubs in the technology field citation network.
- 136 ranked No. 1 in both in-degree centrality and in-closeness centrality, which means that the patents belonging to 136 most frequently cite other patents in different technology fields either directly or indirectly. In particular, 136 is the most important local and global hub in the technology field citation network.
- Following 136, 257, 428, and 438 form the group of secondary patent citation hubs in the technology field citation network.
- 422 is one of the major local hubs, directly citing other patents in different technology fields. Meanwhile, 252 is one of the major global hubs, directly or indirectly citing other patents in different technology fields.

5.3.2.2. Authority analysis. The authority analysis results for the technology field citation network are shown in Table 12. The analysis suggests the following results.

- 136, 428, 257, 313, and 528 are core authorities in the technology field citation network.

Table 13
The top 5 brokers of the technology field citation network.

Rank	Technology field	Betweenness centrality
1	136	0.3259
2	257	0.1010
3	428	0.0879
4	422	0.0540
5	528	0.0470

- 136 ranked No. 1 in both out-degree centrality and out-closeness centrality, which means that the patents belonging to 136 are cited most frequently either directly or indirectly. In other words, 136 is the most important local and global authority in the technology field citation network.
- 428, 257, 313, and 528 are ranked from 2nd to 5th in both out-degree centrality and out-closeness centrality. These technology fields form a group of secondary patent citation authorities in the technology field citation network.

5.3.2.3. Broker analysis. We performed a broker analysis of the technology field citation network by using the betweenness centrality, the results of which are shown in Table 13. The following results were obtained.

- 136 ranked No. 1 in the betweenness centrality analysis and was the most important broker in the technology field citation network.
- Following 136, 257, 428, 422, and 528 were found to play core roles as brokers in the technology field citation network.

6. Conclusions and limitations

This study was undertaken to understand the structure and characteristics of the technological knowledge flow in the field of organic photovoltaic cells and to identify the importance and value of individual nodes. The research framework of the study is outlined in three steps: data collection, network creation, and network analysis. For network analysis, network visualization, network topological analysis, and node centrality analysis were carried out.

The network topological analysis suggests the following results.

- Patent citation networks of three analytical units: countries, institutions, and technology fields, are scale-free networks that follow the power law.

Table A1
The node centrality analysis results of the country citation network.

Country	In-degree centrality	Rank	Out-degree centrality	Rank	In-closeness centrality	Rank	Out-closeness centrality	Rank	Betweenness centrality	Rank
U.S. (US)	0.6538	1	0.8077	1	0.6689	1	0.8138	1	0.3934	1
Japan (JP)	0.4615	2	0.6154	2	0.5495	2	0.6782	2	0.1234	2
Germany (DE)	0.3077	3	0.3846	3	0.4662	3	0.5652	3	0.0243	6
S. Korea (KR)	0.2692	4	0.2308	6	0.4396	4	0.4962	7	0.0099	7
Taiwan (TW)	0.2308	5	0.1538	8	0.4396	4	0.4732	8	0.0022	9
Finland (FI)	0.2308	5	0.1154		0.4274	6	0.4624		0.0018	10
Israel (IL)	0.2308	5	0.0385		0.4274	6	0.3282		0.0026	8
Australia (AU)	0.1923	8	0.1538	9	0.4158	8	0.4732	8	0.0012	
Netherlands (NL)	0.1923	8	0.1154		0.4049		0.4624		0.0008	
UK (GB)	0.1538	10	0.2692	4	0.4158	8	0.5087	4	0.0387	4
Canada (CA)	0.1538	10	0.2308	7	0.4049	10	0.5087	4	0.0615	3
France (FR)	0.1538	10	0.1538	10	0.4049		0.4732	8	0.0359	5
Austria (AT)	0.1538	10	0.1538		0.4049		0.4732	8	0.0012	
Sweden (SE)	0.1154		0.0769		0.3846		0.4423		0.0003	
Switzerland (CH)	0.0769		0.2692	5	0.3752		0.5087	4	0.0000	
China (CN)	0.0769		0.0385		0.3846		0.3335		0.0000	
Greece (GR)	0.0769		0.0000		0.3945		0.0000		0.0000	
Belgium (BE)	0.0385		0.0385		0.3663		0.4329		0.0000	
Italy (IT)	0.0385		0.0385		0.2747		0.4423		0.0000	
New Zealand (NZ)	0.0385		0.0000		0.3855		0.0000		0.0000	
Malaysia (MY)	0.0385		0.0000		0.3855		0.0000		0.0000	
Denmark (DK)	0.0385		0.0000		0.3855		0.0000		0.0000	
Liechtenstein (LI)	0.0385		0.0000		0.3855		0.0000		0.0000	
Singapore (SG)	0.0385		0.0000		0.3462		0.0000		0.0000	
USSR (SU)	0.0000		0.0385		0.0000		0.4521		0.0000	
Argentina (AR)	0.0000		0.0385		0.0000		0.4521		0.0000	
Hungary (HU)	0.0000		0.0385		0.0000		0.3307		0.0000	

Table A2
The node centrality analysis results of the institution citation network (Top 30).

Institution	In-degree centrality	Rank	Out-degree centrality	Rank	In-closeness centrality	Rank	Out-closeness centrality	Rank	Betweenness centrality	Rank
Konarka Technologies	0.0890	1	0.0019		0.2713	1	0.1516		0.0616	4
JX Crystals	0.0290	2	0.0000		0.1566		0.0039		0.0022	
Universal Display	0.0232	3	0.0329	2	0.1948		0.1656		0.0276	7
AU Optronics	0.0174	4	0.0000		0.1827		0.0019		0.0001	
Sharp	0.0155	5	0.0174	5	0.2143	3	0.1909	3	0.0668	3
Showa Denko	0.0135	6	0.0000		0.1698		0.1398		0.0033	
Boeing	0.0116	7	0.0387	1	0.1707		0.2199	1	0.0751	1
Matsushita Electric Industrial	0.0116	7	0.0077		0.1763		0.1685		0.0152	
GE	0.0116	7	0.0039		0.1820		0.1569		0.0184	
Semiconductor Energy Laboratory	0.0116	7	0.0019		0.1810		0.1632		0.0105	
Samsung SDI	0.0116	7	0.0000		0.2133	4	0.0060		0.0014	
Du Pont	0.0116	7	0.0000		0.1733		0.1319		0.0126	
Eastman Kodak	0.0097		0.0155	6	0.2185	2	0.1896	5	0.0682	2
Seiko Epson	0.0097		0.0019		0.2008	5	0.1419		0.0060	
Princeton University	0.0077		0.0155	6	0.1919		0.1518		0.0189	
Canon	0.0077		0.0135	10	0.1322		0.1660		0.0070	
MIT	0.0077		0.0058		0.2003	6	0.1706		0.0526	5
Nomadics	0.0077		0.0019		0.1985	7	0.1280		0.0000	
University of California	0.0058		0.0174	5	0.1579		0.1586		0.0068	
Nokia	0.0058		0.0000		0.1955	10	0.0058		0.0028	
IBM	0.0039		0.0213	4	0.1816		0.2199	1	0.0525	6
Mitsubishi Denki	0.0039		0.0097		0.1459		0.1783	8	0.0059	
Exxon Research & Engineering	0.0019		0.0097		0.0026		0.1907	4	0.0008	
Samsung Electronics	0.0019		0.0019		0.1967	9	0.1202		0.0076	
EPFL	0.0000		0.0290	3	0.1610		0.1744	9	0.0258	8
Motorola	0.0000		0.0155	6	0.0029		0.1875	6	0.0003	
Toshiba	0.0000		0.0116		0.1603		0.1837	7	0.0206	10
Polaroid	0.0000		0.0058		0.0000		0.1734	10	0.0000	
Agilent Technologies	0.0000		0.0019		0.0000		0.1294		0.0000	
KIST	0.0000		0.0000		0.1977	8	0.1544		0.0220	9

Table A3
The node centrality analysis results of the technology field citation network (Top 30).

Technology field	In-degree centrality	Rank	Out-degree centrality	Rank	In-closeness centrality	Rank	Out-closeness centrality	Rank	Betweenness centrality	Rank
136	0.4071	1	0.4513	1	0.4838	1	0.4921	1	0.3259	1
257	0.2566	2	0.2124	3	0.3941	2	0.4116	3	0.1010	2
428	0.2301	3	0.2301	2	0.3889	3	0.4306	2	0.0879	3
438	0.2301	4	0.1327	7	0.3864	4	0.3873	6	0.0451	6
422	0.2035	5	0.0442		0.3521	8	0.3339		0.0540	4
252	0.1770	6	0.0796		0.3839	5	0.3719		0.0228	10
528	0.1416	7	0.1416	4	0.3165		0.4040	4	0.0470	5
313	0.1239	8	0.1416	5	0.3563	7	0.3919	5	0.0116	
310	0.1150	9	0.0177		0.3606	6	0.2196		0.0348	7
359	0.1062	10	0.0796		0.3500	9	0.3719		0.0099	
524	0.0885		0.0796		0.3460	10	0.3538		0.0091	
525	0.0619		0.1062	8	0.3269		0.3828	8	0.0126	
427	0.0619		0.0885	9	0.3324		0.3783	10	0.0071	
548	0.0531		0.0708		0.3269		0.3427		0.0175	
546	0.0531		0.0265		0.3165		0.3339		0.0146	
264	0.0531		0.0177		0.3306		0.3162		0.0000	
564	0.0531		0.0177		0.2755		0.2682		0.0002	
429	0.0354		0.1416	6	0.3036		0.3850	7	0.0102	
106	0.0354		0.0354		0.2521		0.3030		0.0007	
204	0.0354		0.0265		0.3115		0.2821		0.0007	
362	0.0354		0.0089		0.3083		0.2773		0.0003	
430	0.0265		0.0885	10	0.3083		0.3805	9	0.0028	
385	0.0265		0.0442		0.2990		0.3374		0.0000	
526	0.0265		0.0354		0.2990		0.2975		0.0010	
156	0.0265		0.0265		0.3148		0.3339		0.0000	
345	0.0265		0.0265		0.3099		0.3445		0.0000	
423	0.0265		0.0265		0.2975		0.3193		0.0000	
340	0.0265		0.0000		0.3143		0.0000		0.0000	
374	0.0177		0.0089		0.2755		0.3016		0.0330	8
435	0.0177		0.0531		0.2459		0.2517		0.0262	9

Table A4
The USPC Class list of the Top 30 technology fields in the organic photovoltaic cells domain.
Source: Derived from USPTO [47].

Class	Title	Class	Title
136	Batteries: thermoelectric and photoelectric	264	Plastic and nonmetallic article shaping or treating: processes
257	Active solid-state devices (e.g., transistors, solid-state diodes)	564	Organic compounds—part of the class 532–570 series
428	Stock material or miscellaneous articles	429	Chemistry: electrical current producing apparatus, product, and process
438	Semiconductor device manufacturing: process	106	Compositions: coating or plastic
422	Chemical apparatus and process disinfecting, deodorizing, preserving, or sterilizing	204	Chemistry: electrical and wave energy
252	Compositions	362	Illumination
528	Synthetic resins or natural rubbers—part of the class 520 series	430	Radiation imagery chemistry: process, composition, or product thereof
313	Electric lamp and discharge devices	385	Optical waveguides
310	Electric generator or motor structure	526	Synthetic resins or natural rubbers—part of the class 520 series
359	Optics systems (including communication) and devices	156	Adhesive bonding and miscellaneous chemical manufacture
524	Synthetic resins or natural rubbers—part of the class 520 series	345	Computer graphics processing and selective visual display systems
525	Synthetic resins or natural rubbers—part of the class 520 series	423	Chemistry of inorganic compounds
427	Coating processes	340	Communications: electrical
548	Organic compounds—part of the class 532–570 series	374	Thermal measuring and testing
546	Organic compounds—part of the class 532–570 series	435	Chemistry: molecular biology and microbiology

- The measurements of average path length and diameter show that the knowledge transfer processes of three patent citation networks can be more effective than those of a random network of the same size.
- The clustering coefficients are significantly higher in all three citation networks than in a random network of the same size. This fact suggests that nodes in the three citation networks cooperate more closely, exchanging more information than those in the random network.

The critical node analysis using the node centrality indicates that the following facts.

- The U.S., Japan and Germany are the most important local and global hubs as well as the most important local and global authorities, while the U.S., Japan and Canada are important brokers, bridging technological knowledge transfer between countries.
- The hub and authority analysis of the institution citation network indicate that Konarka Technologies is the largest local and global hub and Boeing is the largest local and global authority. The broker analysis displays Boeing, Eastman Kodak, and Sharp are important brokers, bridging technological knowledge transfer between institutions.
- 136, 257, and 428 are the most important local and global hubs, local and global authorities and brokers in the technology field citation network.

The social network analyses presented in previous studies that analyzed the patent citation network were limited to network map drawing or use for network topological analyses. However, in this paper, we proceed one step further by identifying the importance and value of individual nodes adopting various concepts of centrality. We determined that the results from the node centrality analysis and the network topological analysis did not differ. The results of the node centrality analysis clearly show that, in all three patent citation networks, a small number of nodes have the majority of links, while most nodes have only a few links (see Table A1–A3 in Appendix A).

The patent citation network provides insight into the knowledge transfer process at the different levels of respective analytical units, and the directivity of links helps us understand the direction of knowledge flow [30]. The centrality analysis of individual nodes is very useful for measuring the structural location of each node and assessing its importance. Thus, the analytical framework in this paper is applicable to other science and technology domains.

Despite all our efforts to perform an accurate analysis, some inevitable limitations still exist. One is the time lag between a patent and its forward citations. The existence of the time lag means that recently registered patents are likely to display fewer forward citations. Second, the weight (number of citations) is not reflected in the process of network creation. For cases in which more than one citing/cited data exist, we consider that an inflow/outflow link exists between the two nodes. Because of this, it is likely that the importance and value of a critical node are underestimated in the network.

Acknowledgements

This paper was supported by the National Research Foundation of Korea Grant, funded by the Korean Government (NRF-2011-330-B00046).

Appendix A

See Table A1–A4.

References

[1] Ko HC, Lee JK, Oh MA, Lee BR. U.S. and Canada's Green Growth Strategy and Its Implications. Seoul: Korea Institute for International Economic Policy; 2011 In Korean.
[2] Wiesenthal T, Mercier A, Schade B, Petrič H, Szabó L. Quantitative assessment of the impact of the strategic energy technology plan on the European power sector. Luxembourg: Institute for Prospective Technological Studies; 2010.
[3] Solangi KH, Islam MR, Saidur R, Rahim NA, Fayaz H. A review on global solar energy policy. Renewable and Sustainable Energy Reviews 2011;15 (4):2149–63.
[4] IEA. Energy balances of OECD countries. Paris: International Energy Agency; 2008.
[5] New and renewable energy center. New & Renewable Energy Statistics 2010. Seoul: Korea Energy Management Corporation; 2011.
[6] Lee JS, Eo JS, Kim KM, Kim JK. The trend and implication in U.S. renewable industry. Global Business Report. Seoul: Korea Trade-investment Promotion Agency 2008. (In Korean).
[7] Chen C, Hicks D. Tracing knowledge diffusion. Scientometrics 2004;59 (2):199–211.
[8] Stolpe M. Determinants of knowledge diffusion as evidenced in patent data: the case of liquid crystal display technology. Research Policy 2002;31 (7):1181–98.

[9] Karki M. Patent citation analysis: a policy analysis tool. World Patent Information 1997;19(4):269–72.
[10] Archibugi D, Pianta M. Innovation surveys and patents as technology indicators: the state of the art. Innovation, patents and technological strategies. Paris: OECD; 1996.
[11] Wartburg IV, Teichert T, Rost K. Inventive progress measured by multi-stage patent citation analysis. Research Policy 2005;34(10):1591–607.
[12] Basberg BL. Patents and the measurement of technological change: a survey of the literature. Research Policy 1987;16(2):131–41.
[13] Magnusson T, Berggren C. Entering an era of ferment–radical vs. incrementalist strategies in automotive power train development. Technology Analysis & Strategic Management 2011;23(3):313–30.
[14] Ernst H. Patent information for strategic technology management. World Patent Information 2003;25(3):233–42.
[15] Miles I, Andersen B, Boden M, Howells J. Service production and intellectual property. International Journal of Technology Management 2000;20(1):95–115.
[16] Griliches Z. Patent statistics as economic indicators: a survey. Journal of Economic Literature 1990;28(4):1661–707.
[17] Park G, Park Y. On the measurement of patent stock as knowledge indicators. Technological Forecasting and Social Change 2006;73(7):793–812.
[18] Lee S, Kim M. Inter-technology networks to support innovation strategy: an analysis of Korea's new growth engines. Innovation: Management, Policy & Practice 2010;12(1):88–104.
[19] Chang SB, Lai KK, Chang SM. Exploring technology diffusion and classification of business methods: using the patent citation network. Technological Forecasting and Social Change 2009;76(1):107–17.
[20] No HJ, Park Y. Trajectory patterns of technology fusion: trend analysis and taxonomical grouping in nanobiotechnology. Technological Forecasting and Social Change 2010;77(1):63–75.
[21] Huang Z, Chen H, Yip A, Ng G, Guo F, Chen ZK, et al. Longitudinal patent analysis for nanoscale science and engineering: country, institution and technology field. Journal of Nanoparticle Research 2003;5(3):333–63.
[22] Hu AGZ, Jaffe AB. Patent citations and international knowledge flow: the cases of Korea and Taiwan. International Journal of Industrial Organization 2003;21(6):849–80.
[23] Kajikawa Y, Takeda Y. Citation network analysis of organic LEDs. Technological Forecasting and Social Change 2009;76(8):1115–23.
[24] Yoon J, Choi S, Kim K. Invention property-function network analysis of patents: a case of silicon-based thin film solar cells. Scientometrics 2011;86(3):687–703.
[25] Lai K-K, Wu S-J. Using the patent co-citation approach to establish a new patent classification system. Information Processing & Management 2005;41(2):313–30.
[26] Michie J. Introduction. The internationalisation of the innovation process. International Journal of the Economics of Business 1998;5(3):261–77.
[27] Han YJ, Park Y. Patent network analysis of inter-industrial knowledge flows: the case of Korea between traditional and emerging industries. World Patent Information 2006;28(3):235–47.
[28] Narin F. Patent bibliometrics. Scientometrics 1994;30(1):147–55.
[29] Jaffe AB, Trajtenberg M. International knowledge flows: evidence from patent citations. Economics of Innovation & New Technology 1999;8(1/2):105–36.
[30] Li X, Chen H, Huang Z, Roco MC. Patent citation network in nanotechnology (1976–2004). Journal of Nanoparticle Research 2007;9(3):337–52.
[31] Bilke S, Peterson C. Topological properties of citation and metabolic networks. Physical Review E 2001;64(3):036106.
[32] Okamura K, Vonortas NS. European alliance and knowledge networks. Technology Analysis & Strategic Management 2006;18(5):535–60.
[33] Hung S-W, Wang A-P. Examining the small world phenomenon in the patent citation network: a case study of the radio frequency identification (RFID) network. Scientometrics 2010;82(1):121–34.
[34] Brass DJ. Being in the right place: a structural analysis of individual influence in an organization. Administrative Science Quarterly 1984;29(4):518–39.
[35] Friedkin NE. Structural bases of interpersonal influence in groups: a longitudinal case study. American Sociological Review 1993;58(6):861–72.
[36] Burt RS. Structural holes: the social structure of competition. Cambridge (MA): Harvard University Press; 1995.
[37] Baldwin TT, Bedell MD, Johnson JL. The social fabric of a team-based MBA program: network effects on student satisfaction and performance. Academy of Management Journal 1997;40(6):1369–97.
[38] Freeman LC. Centrality in social networks conceptual clarification. Social Networks 1979;1(3):215–39.
[39] Nelson AJ. Measuring knowledge spillovers: what patents, licenses and publications reveal about innovation diffusion. Research Policy 2009;38(6):994–1005.
[40] Albert R, Barabási AL. Statistical mechanics of complex networks. Reviews of Modern Physics 2002;74(1):47–97.
[41] Cyram. NetMiner help. Seoul: Cyram; 2010.
[42] Clauset A, Shalizi CR, Newman MEJ. Power-law distributions in empirical data. SIAM Review 2009;51(4):661–703.
[43] Mizruchi MS, Marquis C. Egocentric, sociocentric, or dyadic? Identifying the appropriate level of analysis in the study of organizational networks Social Networks 2006;28(3):187–208.
[44] Sohn DW. Social network analysis. Seoul: Kyungmoon; 2008.
[45] Freeman LC. A set of measures of centrality based on betweenness. Sociometry 1977;40(1):35–41.
[46] Kim KT, Kim YH. The understanding of U.S. patent classification. Patent 21. Seoul: Korea Institute of Patent Information; 2008. (In Korean).
[47] USPTO. Classification Information, ⟨http://www.uspto.gov/web/patents/classification⟩ 2012 (accessed March 2012).