

# A Structured Approach to Locate the Technological Position by Technology Knowledge Redundancy — Patent Citation Network Perspective

*Horng-Jinh Chang<sup>1</sup>, Hsueh-Chen Chen<sup>1</sup>, Yu-Hsin Chang<sup>2</sup>, Vimal Kumar<sup>2</sup>,  
Chien-Yu Lin<sup>2</sup>, and Yi-Ru Lee<sup>3</sup>*

<sup>1</sup>Tamkang University, <sup>2</sup>Chaoyang University of Technology Taichung and  
<sup>3</sup>Yunlin University of Science and Technology

## Abstract

This study approaches the relative position of a company in technological network based on patent citation of the cloud computing industry. It integrates the PCA with the patent family to obtain a complete data set for later analysis. After that, the Technology Knowledge Redundancy in the PCN has  $TKS/TKR$  indicators for analysis. Moreover, the changes in the technological positions before and after patent transfer revealed three patent acquisition strategies namely: strengthening foothold by enhancing barriers, a cash cow for non-practicing entities (NPE), and a shortcut for peripheral and new entrants. After patent transfer, more companies obtained high and low positions in the technological network and gained abundant and decreased resources. This fact reveals that the unchanged dichotomy in technological transfer. In order to obtain high positions in the technology industry and gain cooperation opportunities, marginal or new entrants of the technological field would need to acquire patents with high  $TKS/TKR$ .

*Keywords:* Patent citation network, patent co-citation approach, technological knowledge status, technological knowledge reliability, technology redundancy..

## 1. Introduction

For technology-intensive industries, the rapid expansion of the ability to innovate is a key element in maintaining long-term competitiveness. Corporate mergers and acquisitions of other patented technologies are the most common methods for expanding innovative abilities (see Hagedoorn [10] and King et al. [13]). When the technological resources of potential partners or acquisition targets are rich and diverse, companies are more likely to choose mergers and acquisitions than other methods to obtain the desired knowledge or technology (see Villalonga and McGahan [28]). However, such an acquisition is not a panacea for rapid access to the new technology.

When the technology gap between the new technology obtained by the firm and its original technology is too great, the firm's ability to absorb new knowledge may be affected. By the same token, when the similarity between the new technology and the firm's original technology is too high, innovation performance may also be greatly reduced (see Ghoshal [6] and Hitt et al. [12]).

Consequently, companies must clearly understand and evaluate the desired technology resources and select cooperation or merger partners to effectively achieve their strategic purposes, in order to enhance innovation performance after the acquisition of the new technology. Further, how firms analyze their own and their competitor's technologies and position in technology networks, as a basis for assessing future patent acquisition, transfer, and targets for cooperation, in order to successfully obtain the required patented technology and achieve strategic objectives, is critical. Therefore, firms should consider how to use patent acquisition strategies and identify shifts in technology among groups of firms in the industry, as well as how to effectively use patent analysis to locate valuable technology resources.

Patent citations not only reveal flows of knowledge and technologies, commonalities of knowledge (see Podolny and Stuart [23]), and the market value of technologies, they also reveal the layout of technology development strategies and cooperative relationships between firms. By following the direction of patent citations and links, the technological dependency relationships between firms may be illuminated, enabling elucidation of the structure of technological networks, which are similar to social networks. From the decision-making point of view, the results of a patent citation analysis may enable the firm to make judgments about partner firms for cooperation and provide a basis for patent acquisition (see Breitzman and Thomas [1] and Park and Yoon [22]). Moreover, a broad technology network analysis can illuminate the overall social structure of actors in the technology network, their relative positions, and their relationships and roles (see Podolny et al. [24], Stuart [26], Yoon and Park [33], Breschi and Lissoni [2] and Makri et al. [20]).

Scholars have assessed technological competencies using patents in several ways; among these include patent counts and the indicators produced by them, patent portfolio, patent citation and the indicators produced by them, and patent citation network analysis (see Park and Yoon [22], Yoon and Park [33], Podolny et al. [24] and Stuart and Podolny [27]). Chen and Lai [4] have proposed the use of Technological Knowledge Status (*TKS*) and Technological Knowledge Reliability (*TKR*) based on patent citation networks as indicators to effectively locate a company's position within a technology network in a knowledge-relationship niche plot.

Patent citation networks structured with social network analysis helps us understand the overall relationship among patents (see Weng and Lai [31], Breschi and Lissoni [2], Yoon and Park [33], Stuart and Podolny [27] and Kumar et al. [15]). It can be used to analyze the position of a company in a network. Recent studies on organizations belonging in a group have used the viewpoints of social networks to perform structured analysis (see Cantner and Graf [3], Von et al. [29], Yoon and Park [31] and Gulati [9]).

A patent citation network divides patents into citing patents and cited patents. As shown in Figure 1, a network can be seen as a two-mode network with two different sets of patents, one being senders (citing patents) while the other being receivers (cited patents). Figure 2 demonstrates that cited patents belonging to the same company can be grouped together forming an affiliation matrix of patents. Patents 1 and 2 belong to Company A. Patents 3, 4 and 5 cite Company A's patents; therefore, Patents 1, 2, 3, 4 and 5 are all affiliated to Company A. Through the calculation of network affiliations, the relationship between companies can be better understood and a company's position can be easily located within a network.

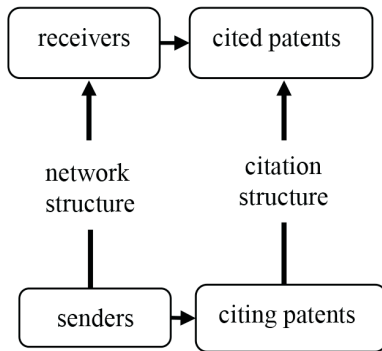


Figure 1: The two-model Patent Citation Network

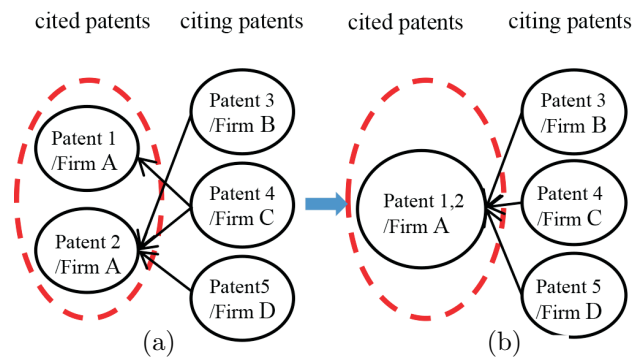


Figure 2: A sketch Map for Patents Affiliation to Companies

In a patent citation network, the patent citations can be seen as interrelated technological knowledge; therefore, a patent citation network can be regarded as an associative network of technological knowledge. Two indicators, the  $TKS$ , and  $TKR$  can be used to analyze the associative network.  $TKS_{ii}$  represents the overlap of technological knowledge within Company  $i$ . The bigger the overlap, the greater the investment the company has put into the research of a given technology. The company, therefore, is producing more patents and the technology that it is developing is unique.  $TKR_{ij}$  represents the overlap of the technological knowledge between Company  $i$  and Company  $j$ . It reveals the strength of the  $TKR$ , i.e. the correlation between the two companies. The two indicators can then mark the position of a company in the technological knowledge-relationship niche plot (see Lai et al. [18] and Chen and Lai [4]); which is a simple but an effective way to analyze the technological status of a focal company.

In an associative network of technological knowledge, the  $TKS$  and  $TKR$  can be used to construct a technological knowledge-relationship niche plot to analyze positions and roles of companies.

This study aims to build an assessment model combining three terms PCA, TS and  $TKS/TKR$  to use in the ITS system. PCA used to assess the similarity of patents based on the number of times the patents are co-cited and serves as a tool to categorize patents (see Lai and Wu [17]) while TS method helps to categorize patents into different clusters and measure cumulative  $R$ -square values. Glover and Laguna [7] and Chen and Lai [4]

have proposed the use of  $TKS$  and  $TKR$  based on PCNs as indicators to effectively locate a company's position within a technology network in a knowledge-relationship niche plot. In this way, its technical position, as well as its competitors, in a technology network, will be known; and operational strategies based on the results and analysis can be formulated.

## 2. Methodologies and Model Construction

The construction of a model involved three phases as shown in Figure 3. These are (1) establishment of a preliminary patent database, (2) patent classification, and (3) Technology Knowledge Redundancy. The steps undertaken for these phases are further described below, as shown in Figure 3. The first phase dealt with information retrieval and database establishment. During this phase, related categories of technology were defined with literature and technical reports in order to set keywords for retrieval. Having retrieved those keywords, a preliminary database  $\Omega$  for patents was established. Later, patents that are not related to the technology field studied here were removed, by which the patent dataset  $\Omega'$  was set up. Patent dataset  $\Omega'$  might contain technologies of different properties, which could not be distinguished easily.

Phase 2, in order to choose the technologies more precisely, was necessary to categorize technologies. The patents of the database were divided into "Target Patents" (citing patents)  $Q_i, i = 1, 2, \dots, M$  to be classified and "Candidate of Basic Patents" (cited patents)  $P_j, j = 1, 2, \dots, N$  that were basic patent candidates. The citation relationships were used to establish a network matrix for patent citations. The related technology fields involved in the patent dataset were classified with the methods of Patent Co-citation Approach (PCA) (see Lai and Wu [17]) and Tabu Search (TS) (see Glover and Laguna [7]).

In the last phase, the patent citation network formed by patents of the chosen technological fields was analyzed. The two indicators,  $TKS$ , and  $TKR$  were used to construct a model for patent assessment. The model was established, hoping to assess companies technological competencies and their positions in the technology network. Also, the model was used to analyze the technological positions formed by the two indicators.

### Phase 1: Establishment of a Preliminary Patent Dataset

The latest technology is often fully revealed after patent application. Consequently, a patent dataset contains a great deal of information about technological development and exclusive rights. Patent information can be an indicator of technological development (see Chen and Lai [4], Hall et al. [11], Lai and Wu [17], Griliches [8], Narin et al. [21] and Kumar et al. [16]). The technology industry views technological development as highly confidential. Against this background, patent analysis can serve as an important tool to study technological development. On the other hand, many experts and leading companies of the industry have varied definitions of new emerging technologies. Moreover, the market and the industry use different formal names for the same concept. This situation makes it necessary to choose keywords carefully before patent retrieval is done.

In order to establish a proper patent information dataset, two steps were executed which are explained below: The first step was that a thorough retrieval was conducted based on a given industry, in hopes of finding out existing patent information. The second step was the selection and verification of the dataset, during which the patents unrelated to the field were removed to create a dataset with more precise information.

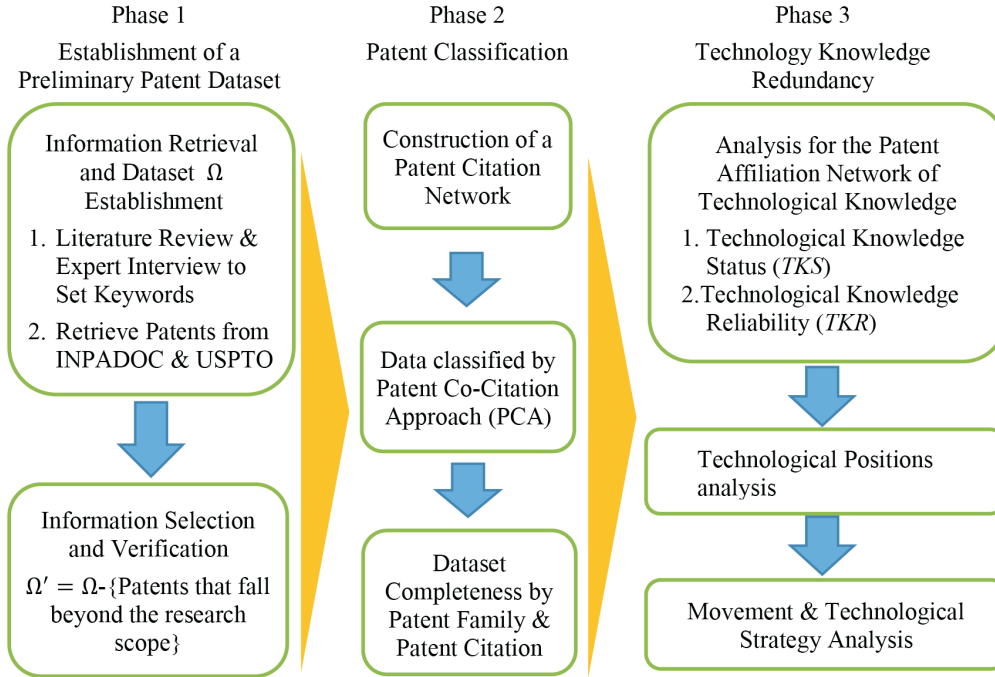


Figure 3: Research Framework.

#### Step 1: Information Retrieval and Dataset Establishment

A thorough patent retrieval was conducted based on a given industry in the search for existing patent information. Keywords were first generated by using literature review, examination of news and internet research. Keywords were then added or deleted based on expert interviews. Retrieval was conducted in the dataset of International Patent Documentation (INPADOC) and the United States Patent and Trademark Office (USPTO), with the limitations of application dates, publication dates, patent issue dates, etc. Using Boolean operators (AND, OR, and NOT), the keywords were set for retrieval. In this way, a preliminary patent information dataset  $\Omega$  was set up.

#### Step 2: Information Selection and Verification

Unrelated patents to the field were removed in this step to create a database with more precise information. The information obtained in dataset  $\Omega$ , have been carefully read and discriminated, revealed that some patents fell beyond the scope of this study. Therefore, these patents were removed after verification of industrial information carefully. Then, the remaining keywords were used for another process of retrieval and the

correct preliminary dataset  $\Omega'$  was set up.

$$\Omega' = \Omega - \{\text{Patents that fall beyond the research scope}\} \quad (2.1)$$

### Phase 2: Patent Classification

The citation relationships were used to develop a matrix for patent citation networks. The patent dataset  $\Omega'$  obtained in phase 1 contained technologies with different properties that were not easily distinguishable. Consequently, technologies were categorized using Patent Co-citation Approach (PCA) and Tabu Search (TS) (see Lai et al. [18] and Lai and Wu [17]). Both were also used to identify technological clusters. If the number of a patent cluster in the dataset was not sufficient for analysis, then retrieval was conducted again to expand the dataset with patent family and citation relationships. The steps utilized for this phase are further explained below.

#### Step 1: Construction of a Patent Citation Networks (PCNs)

PCNs were formed by patents and the corresponding citation relationships. Each patent regarded as a node, while patent citations as relationship ties (see Podolny et al. [24] and Stuart and Podolny [27]). After making a careful selection of the patents in the dataset  $\Omega'$  were divided into Target Patents (citing patents) and Candidate of Basic Patents (cited patents). The Target Patents had  $M$  patents, denoted by  $Q_i, i = 1, 2, \dots, M$ , while Candidate of Basic Patents had  $N$  patents, denoted by  $P_j, j = 1, 2, \dots, N$ . The citation relationship between  $Q_i$  and  $P_j$  is represented by the matrix  $[\alpha_{ij}]_{M \times N}$ , as shown in (2.2).

$$[\alpha_{ij}]_{M \times N}, \quad \alpha_{ij} = \begin{cases} 1, & Q_i \text{ cites } P_j \\ 0, & \text{otherwise} \end{cases} \quad i = 1, 2, \dots, M, \quad j = 1, 2, \dots, N \quad (2.2)$$

The frequency  $c$  was defined as the critical value for the Candidate of Basic Patent, where any patent  $P_j$  that were cited less than  $c$  times were removed. The remaining patents in  $P_j$  were then regarded as basic patents. For convenience, denoted all basic patents by  $P_j, j = 1, 2, \dots, n$  and the correspondent citing patents denoted by  $Q_i, i = 1, 2, \dots, m$ . The citation relationships between basic patents  $P_j$  and  $Q_i$  formed a new matrix  $[\varepsilon_{ij}]_{m \times n}$ , as shown in (2.3). Therefore,  $m \leq M, n \leq N$ , and  $m \geq n$ . The number of basic patents  $n$  can be influenced by the frequency  $c$ . The bigger value of  $c$  makes the smaller number of  $n$  and  $m$ .

$$[\varepsilon_{ij}]_{m \times n}, \quad \varepsilon_{ij} = \begin{cases} 1, & Q_i \text{ cites } P_j \\ 0, & \text{otherwise} \end{cases} \quad i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \quad (2.3)$$

#### Step 2: Patent Co-citation Approach (PCA)

Patent Co-citation Approach (PCA) originated from the concept of co-citation, which measures the frequency of any two documents being cited together by other documents (see Small [25]). It is used to assess the similarity of patents based on the number of times the patents are co-cited. It serves as a tool to categorize patents (see Lai and

Wu [17]). Patent classifications, such as the International Patent Classification (IPC), updates relatively slow and the technological fields that it defines do not coincide well with the industry. Meanwhile, the United States Patent Classification (UPC) updates relatively quickly but the technological fields that it defines cover quite a narrow range, which classifies some patents into different categories. The PCA, however, has a relatively small number of patents that are classified into different categories than the UPC. Moreover, the technological fields that define show remarkable consistency with the industry's technological development (see Wu [32]). Even though the PCA is better than the IPC and the UPC, the PCA does have two potential disadvantages. One is that repeated patent classifications might happen, which would need further manual sorting and classification. The other is that the PCA is not fit for the analysis of a dense network (see Wu [32]). Chen et al. [5] opposed the factor analysis the PCA had been adopted; instead of classified patents and measured  $R$ -square using the TS method by first setting the number of technological clusters (see Glover and Laguna [7]). The approach he used is based on Pearson's correlation coefficient matrix  $[\gamma_{jj'}]_{n \times n}$ . The TS method employs local search methods for mathematical optimization (see Glover and Laguna [7]). In this study, the most suitable number of clusters was decided based on the variability and stability of the cumulative  $R$ -square values for technological clusters.

The frequency of every two basic patents being co-cited is used to evaluate the similarity between basic patents. Using,  $[\omega_{jj'}]_{n \times n}$ , the matrix for the co-citation of the basic patents  $P_j$  and  $P_{j'}$ , was developed (see Lai and Wu [17] and Wu [32]). This is shown in equation (2.4).

$$\omega_{j,j'} = \begin{cases} \sum_{i=1}^m \varepsilon_{ij} \varepsilon_{ij'}, & \text{if } j \neq j' \\ 0, & \text{if } j = j' \end{cases} \quad j = 1, 2, \dots, n, \quad j' = 1, 2, \dots, n \quad (2.4)$$

The correlation coefficient was calculated using the Ucinet software with the matrix  $[\omega_{jj'}]_{n \times n}$ , and its diagonal value being removed. In this way, the similarity in the basic patents, which was represented by the Pearson correlation coefficient matrix,  $[\gamma_{jj'}]_{n \times n}$ , was obtained. With this obtained matrix and the number of technological clusters set beforehand, the TS method was utilized to categorize patents and measure cumulative  $R$ -square values. The scree plot was used to demonstrate where the scree plot started leveling off, and the groups whose values were in the level part were removed. The remaining groups were carefully read and collated, with the peculiarity of their technological content examined. The results were then discussed with technical consultants and the patent clusters were named.

### Step 3: Dataset Completeness

Patent citations and patent family can be used to increase patent counts if basic patents are insufficient. A dataset was established based on the basic patents and the concepts about patents. In addition, the information about the patent family was added to the dataset to complete the information on technological fields. Among the groups with their corresponding names obtained from the results of the first analysis, one cluster was chosen for study. The patent family was identified with the basic patents of the

cluster through the INPADOC. Patent numbers were used on Google Patent Search to retrieve the Target Patent and Candidate of Basic Patent forming a complete technological network. Next, the Ucinet software was used to draw the matrices that represent the network and the analysis was performed by drawing on related information.

### Phase 3: Technology Knowledge Redundancy

Two indicators the *TKS* and the *TKR* were used to analyze the technological network. Patent affiliation networks are an extension of social affiliation networks. The social affiliation network is a relational network in which actors are affiliated to some social events (see Wasserman and Faust [30]).

#### Step 1: Patent and Technological Knowledge Affiliation Matrix of Firm

At first, the dichotomy is used, with “1” being an affiliation relationship between a company and its patents in terms of technological knowledge and with “0” being no such relationship. Suppose there is a technological knowledge network that contains nine patents (Patent 1-9) belonging to six companies (Firm A-F). Where Firm A possesses Patent 1, namely (Firm A, Patent 1) = 1. In addition, Patent 1 is cited by three patents, namely Patent 4 of Firm D, Patent 5 of Firm D, and Patent 8 of Firm E, i.e. (Firm A, Patent 4) = 1, (Firm A, Patent 5) = 1, and (Firm A, Patent 8) = 1. Therefore, a matrix is established, which reveals the affiliation of technological knowledge between a patent and its company according to the requirements of the aforesaid companies on the *TKS* indicators, as shown in Table 1. By analogy, the affiliation matrix between companies and patents regarding technological knowledge can be obtained.

Table 1: Patent and Technological Knowledge Affiliation Matrix of Company.

	Firm					
	A	B	C	D	E	F
Patent 1	1	0	0	0	0	0
Patent 2	0	1	0	0	0	0
Patent 3	0	0	1	0	0	0
Patent 4	1	1	0	1	0	0
Patent 5	1	0	1	1	0	0
Patent 6	0	1	0	1	0	0
Patent 7	0	1	1	1	0	0
Patent 8	1	1	0	1	1	0
Patent 9	0	0	0	1	0	1

Table 2: Technological Knowledge Reliability Matrix between Companies.

	Firm					
	A	B	C	D	E	F
Firm A	–	2	1	3	1	0
Firm B	2	–	1	4	1	0
Firm C	1	1	–	2	0	0
Firm D	3	4	2	–	1	1
Firm E	1	1	0	1	–	0
Firm F	0	0	0	1	0	–



### Step 2: Constructing Patent Affiliation Network Dataset

A patent affiliation network is the extension of a social affiliation network. The social affiliation network is a relational network in which actors are affiliated to major social events (see Wasserman and Faust [30]). Patent affiliation networks are affiliation relations between patents and companies, as shown in equation (2.5).

Further analysis of Equation (2.4)  $[\omega_{jj'}]_{n \times n}$  leads to patents and companies, which can be used to define the affiliation matrix  $B$ , i.e.  $B = [\beta_{kr}]_{n \times h}$ ,

$$\beta_{kr} = \begin{cases} 1, & \text{if patent } k \text{ is affiliated to company } r \\ 0, & \text{otherwise} \end{cases} \quad k = 1, 2, \dots, n, \quad r = 1, 2, \dots, h, \quad n \geq h \quad (2.5)$$

where:  $n$  represents the patent counts in a network,

$h$  represents the number of companies in a network.

Let  $B^T$  be the transpose of matrix  $B$ , i.e.  $B^T = [\beta'_{rk}]_{h \times n}$ ,  $\beta'_{rk} = \beta_{kr}$ . Then,  $TKS$  and  $TKR$  are as follows (2.6).

$$B^T B = \begin{bmatrix} TKS_{11} & TKR_{12} & \cdots & TKR_{1h} \\ TKR_{21} & TKS_{22} & \cdots & TKR_{2h} \\ \vdots & \vdots & \vdots & \vdots \\ TKR_{h1} & TKR_{h2} & \cdots & TKS_{hh} \end{bmatrix} \quad (2.6)$$

where

$$TKS_{ii} = \sum_{k=1}^n \beta'_{ik} \beta_{ki}, \quad i = 1, 2, \dots, h, \quad (2.7)$$

$$TKR_{ij} = \sum_{k=1}^n \beta'_{ik} \beta_{kj}, \quad i, j = 1, 2, \dots, h \text{ and } i \neq j. \quad (2.8)$$

### Step 3: Analysis for the Patent Affiliation Network of Technological Knowledge

#### Indicator 1: Technological Knowledge Status ( $TKS$ )

The  $TKS$  of each company in a technological network was obtained. The general formula is shown in equation (2.7) (see Chen and Lai [4]).

$TKS_{ii}$  represents the sum of the overlap of Company  $i$ 's patents, i.e. the diagonal value of the matrix  $[TKS_{ii}]$ .

#### Indicator 2: Technological Knowledge Reliability ( $TKR$ )

To calculate the  $TKR$  of the company in the technological knowledge network, we refer to the affiliation matrix in Table 1 as the input. Firm A's affiliated patents are patent 1,4,5,8, and Firm B's affiliated patents are patent 2,4,6,7,8. The patents affiliated to both Firm A and Firm B are patents 4,8, i.e.  $TKR$  (Firm A, Firm B)=2. By analogy, the  $TKR$  matrix between companies in the whole technology network is shown in Table 2.

Due to the overlap of technological knowledge within two different companies in a technology network, the  $TKR$  matrix can be obtained. The general formula is represented in equation (2.8) (see Chen and Lai [4]).

$[TKR_{ij}]$  represents the sum of the overlap of the associative patents of Company  $i$  and Company  $j$ .

Lastly, in order to counterbalance the influence of patent counts that Company  $i$  owns on the company's  $TKR$ ,  $[TKR_{ij}]$  was divided by the patent counts affiliated with the company, i.e. the value of the  $TKS$  for each company. The resulting quotient was identified as the value of the  $TKR$  for an individual company in a whole network. To obtain the  $TKR$  for each company in the whole technological network, equation (2.9) was used (see Chen and Lai [4]).

$$TKR_{ii} = \frac{\sum_{j=1}^h TKR_{ij}}{TKS_{ii}} \quad i = 1, 2, \dots, h, \quad j = 1, 2, \dots, h, \quad i \neq j. \quad (2.9)$$

After the construction of the model, the study used to test the Intelligent Transportation System (ITS) that can be utilized to effectively locate the technological position of a company. It suggests that the model can effectively locate the technological positions of the ITS companies. In addition, the changes in the technological positions before and after patent transfer revealed three patent acquisition strategies namely, (1) strengthening foothold by enhancing barriers, (2) a cash cow for non-practicing entities (NPE), and (3) a shortcut for peripheral and new entrants.

### 3. Case and Discussion

The above-mentioned model for assessment was used for the analysis. This study analyzed the Cloud Computing and Intelligent Transportation System (ITS), to understand the properties of technological status and the centralities in a technological network for intelligent transportation systems. Further, the implications of the strategies used that changed the technological status and centralities before and after the patents were transferred were also analyzed.

#### (1) Cloud Computing and the ITS

The word 'Cloud Computing' first appeared at the Google Search Appliance (GSA) Conference in 2008. Its implications were generated after the Internet bubble. The word surfaced in the recent ten years. Cloud Computing is a peculiarity of virtual computing software. Previously, scholars have put forward Moore's Law for hardware updates. According to the law, the IC technology gains an updated generation every year and a half. If the law applies to software update, the refresh rate will be faster. Generally speaking, patents for inventions are reviewed every 3 to 5 years. Business owners often apply for patents beforehand because the patent application for an invention can be done as long as it is novel, original, and applicable for the industry.

The ITS integrates electronic, communications, computer, control and sensing technologies into all kinds of transportation systems, especially transportation by land. Traffic problems can be improved by real-time information transmission, which increases safety, promotes efficiency and improves service. The development of the ITS began early, especially satellite positioning and Geographic Information System (GIS). With two to three decades of infrastructure construction and widespread use of their applications, intelligent transportation systems provide various types of service, such as the provision of real-time traffic information, vehicle fleet management, and electronic toll collection. The service of Google Maps provided in 2005 by Google and the improvement of network speed enabled a closer connection between Google Maps and people's daily life. Moreover, easier access to image information and more mature navigation technology prompted companies to invest in the development of traffic information platforms. Big data based on Cloud computing technology are being used to incorporate traffic data and real-time feedback from users, providing solutions and creative service for intelligent transportations by integrating all kinds of service. The popularity of smart products and the maturity of Cloud computing technology increased people's interaction with smart transportation systems. Through bilateral interaction of information and flexible traffic management, personalized journey, rescue for live traffic problems, and additional transportation service can be achieved.

## (2) Analysis of Cloud computing and the ITS

### Phase 1: Establishment of a Preliminary Patent Database

Recently, the Cloud computing industry is flourishing. Experts, scholars, and leading companies of the industry have varied definitions for the word Cloud. Moreover, the Cloud computing market and industry use different proper names for Cloud. The situation necessitates a careful selection of keywords for patent retrieval. The creation of a database consisted of two phases: first, a thorough search for the features of Cloud industry was done to determine all patent data about the Cloud industry; for the second phase, data from the dataset were selected and verified to set up a Cloud patent dataset with precise data.

### Step 1: Information Retrieval and Dataset Creation

Initially, Cloud, a widely defined word by Google, was used as a basis for retrieval. Keywords were summarized after referring to academic articles and related international websites like the American National Standards Institute and consulting some experts. The keywords included "SPEC/Cloud" and ( "comput\$" or "brows\$" or "service" or "system" or "web\$" or "communicat\$" ). In addition, patent specifications released between 2003 and 2014 were also retrieved. At the first phase, there were 16, 285 patents, which constituted the preliminary cloud dataset  $\Omega_{\text{cloud}}$ .

### Step 2: Information Selection and Verification

Some retrieved patents were found to fall beyond the research scope of this study after the above-mentioned information was perused, like "cloud point", "electron cloud",

Table 3: Deleted keywords that fall beyond “Cloud”.

Sharpening	cleaning an ion source	cloud point	cloud chamber
point cloud	quadruple ion	oligonucleotide	heart cavity
vaccinating	segmented-ion	n-alkanes	endocardium
pyridine	hydrofluorocarbon	olefins	point cloud
radiation	ion-ion reactions	microalgae	polysaccharides
atom	bimannual	fatty acid	glycol
cycloparaffin	dust cloud	electron cloud	silane
toner	estolide	colorant	oligonucleotides
benzoic	Detergent	steam	polypeptides
ion cloud	cloud point	catheter	solar insolation
paraffinic	oligonucleotide		

and “point cloud” . Those words were often used in the patents of the chemical or material industry. For the sake of precision and correctness of the data, the 42 sets of keywords were removed, which is shown in Table 3. Moreover, the data were verified for correctness with the help of related industrial information. After selection, the dataset  $\Omega_{\text{cloud}}$  obtained 9,760 patents, and the database was named *Basic Dataset for Major Cloud Technologies*  $\omega_{\text{cloud}}$ .

## Phase 2: Patent Classification

### Step 1: Patent Citation Network

The matrix for the patent citation network  $[\alpha_{ij}]_{9760 \times 9760, \text{cloud}}$  was developed based on the citation relationships included in the 9,760 patents of the database  $\Phi_{\text{cloud}}$ . The patents that were never cited were deleted; while those that were cited more than twice were kept. After selection, the citation relationships of the remaining 535 patents were used to make a patent citation matrix  $[\varepsilon_{ij}]_{535 \times 535, \text{cloud}}$ ; the column matrix consisted of Citing Patent Target Patents while the row matrix consisted of Cited Patent Candidate of Basic Patents. Due to the limitations of the matrix size ( $256 \times 256$ ) for Ucinet software, the patents listed in the column matrix as well as in the row matrix were removed if they were never cited. Consequently, a new matrix  $\omega_{\text{cloud}} = [\varepsilon_{ij}]_{148 \times 89, \text{cloud}}$  with  $148 \times 89$  patents was developed. After, classification with the PCA was conducted.

### Step 2: Patent Co-citation Approach (PCA)

This study used the PCA proposed by Lai and Wu [17], and the TS method by Glover and Laguna [7] to classify patents into different clusters. The scree plot and the ranges of small  $\Delta R$ -square values were utilized to set the number of clusters. The result of the number of basic patent clusters of technologies is shown in Figure 4. The

comparison between patent clusters and high range of  $R$ -square values showed that the most suitable number of the cluster for this study is 11. The 11 clusters were named based on the abstracts of patent files and on expert opinions; the naming scheme is shown in Table 4.

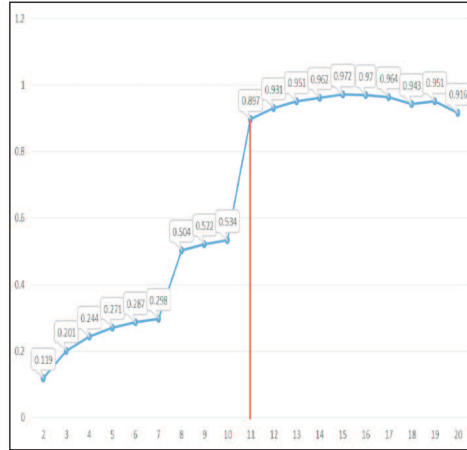


Figure 4: The number of basic patent clusters of important technologies and  $R$ -square.

Table 4: The 1st-phase Patent Clusters & Naming.

Cluster	Technology	Count
TF01	Environmental sensing technology	5
TF02	Mobile location technology	6
TF03	Cloud data transmission technology	17
TF04	Safety monitoring system technology	7
TF05	Community interaction (games) rules	6
TF06	Data management and service system	16
TF07	Customized service technology	5
TF08	Critical point detection technology	6
TF09	Path optimization for dynamic flows	6
TF10	Speech recognition technology	10
TF11	Traffic monitoring technology	5

## Step 3: Dataset Completeness

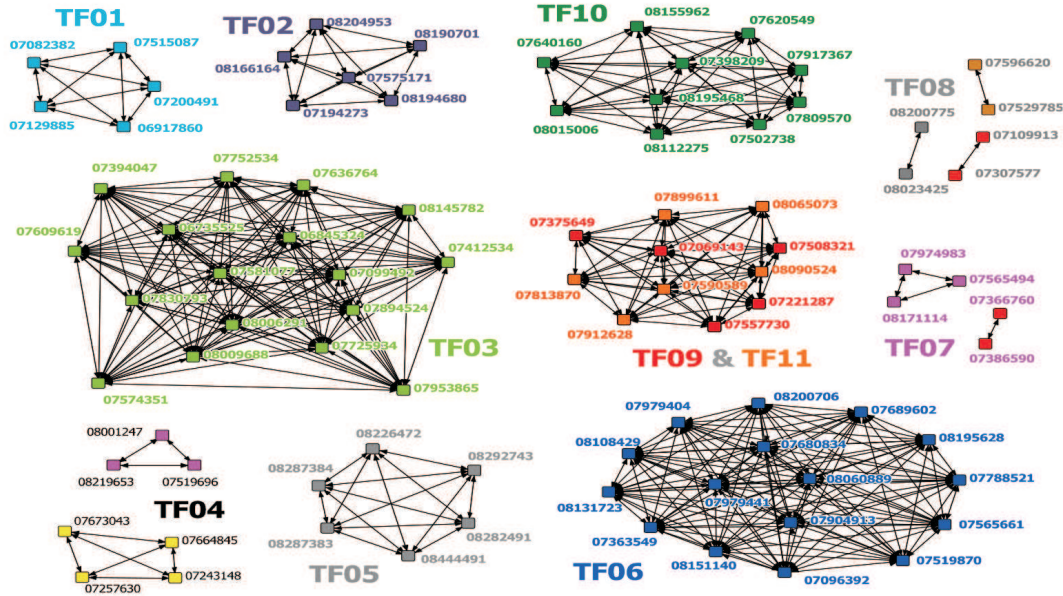


Figure 5: Patent data collection of the first phase and structure charts for the relevance of patent clusters.

Figure 5 shows that the network structures of TF09 (path optimization) and TF11 (data monitoring) are closely related to each other which reveals the considerable relevance of the two technologies. TF11 focuses on applied technology of traffic information while TF09 is mainly involved in the prediction of dynamic flows of statistical algorithms. The two technologies both belonged to the ITS. The ITS is a new emerging technology and therefore has a limited number of patents. A patent database was created through a patent family search of the two basic patents, and through the inclusion of cited and citing patent. After, public data was used to obtain the industrial development profile.

For cluster TF09, six patents regarding path optimization of dynamic flow technology were included. The 11<sup>th</sup> cluster TF11 consisted of 5 patents about data information monitoring. The 11 patents of the two groupings were used to search for their patent family in the database INPADOC, during which, 29 patents were retrieved; while 463 cited and citing patents were obtained through Google Patent Search.

The 463 patents constitute the database  $\omega_{ITS}$  in which, information were used to analyze the ITS. The patent citation network matrix  $[\alpha_{ij}]_{463 \times 463, ITS}$  was developed with the database  $\Phi_{ITS}$ . After, the patents that were cited less than 4 times were removed, and the citation relationships of the remaining 278 patents were used to develop a patent citation network  $[\varepsilon_{ij}]_{278 \times 278, ITS}$ . One key point was the citation counts among the patents; therefore, in the matrix,  $[\varepsilon_{ij}]_{278 \times 278, ITS}$ , 88 cited patents that were cited less than twice and 78 citing patents that were never cited were removed. The matrix  $[\varepsilon_{ij}]_{278 \times 278, ITS}$  was then revised into  $\omega_{ITS} = [\varepsilon_{ij}]_{210 \times 190, ITS}$  for observation and further analysis. Based

on the TS, the number of groupings needed for this study is 4; therefore, the patents were divided into 4 groupings. The corresponding naming scheme of the clusters based on the abstracts of patent files and expert opinions is shown in Table 5. The scree plot and the ranges of  $\Delta R$ -square values were utilized to set the number of clusters. Figure 6 represents the comparison between patent clusters of the ITS technologies and  $R$ -square values. The way to find the set of clusters through scree plot and ranges of  $R$ -square values is same to Figure 4. The comparison between patent clusters and high range of  $R$ -square values showed that the most suitable number of the cluster for this study is 11.

Table 5: The 2nd-phase Patent Clusters & Labeling.

Cluster	Technology	Count
2-TF1	Basic technologies for vehicular communication systems	66
2-TF2	Message transmission/ broadcasting technology	25
2-TF3	Technologies of dynamic path flow prediction and analysis	9
2-TF4	Vehicle information retrieval technology	110

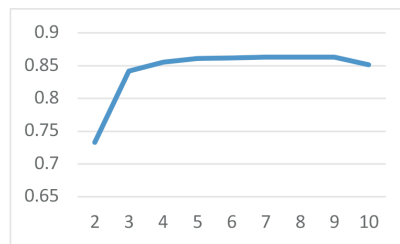


Figure 6: Comparison between patent clusters of the ITS technologies and  $R$ -square values.

### Phase 3: Technology Knowledge Redundancy

This study observed the technological network before and after the patents were transferred to understand the technological status and the implications for management of the associative networks of technological knowledge (the  $TKS$ ,  $TKR$ ) and patent citation network analysis. The patent is proxy for technology (see Weng and Lai [31]), relation between patent represent relation between technology. The redundancy of patent information shows the technology knowledge redundancy.

#### Step 1: Analysis of the Patent Affiliation Networks of Technological Knowledge

The changes in the status before and after the patents were transferred can be seen in the position of a company in the knowledge-relationship niche plot (depicted in Figure 7), which is made up of the two axes namely: the  $TKS$  and the  $TKR$  that are used to analyze the technological network. The  $TKR$  and  $TKS$  values represent the degree of technology redundancy between companies. Technology knowledge redundancy is a powerful concept

of strength of similar cord between adjacent technologies or companies. The degree of redundancy in technology constitutes a measure of technology knowledge sharing between two companies (see Kumar et al. [14]). Figure 7 shows that some companies that had low values of  $TKS$  before the transfer exited the field with strategic restructuring. On the other hand, some companies acquired patents from other companies to improve their technological status and continued competing with others in the same field.

### Step 2: Analysis of the Values of the Indicators

The two indicators namely,  $TKS$ ,  $TKR$  were marked (+) if their values were higher than the averages; otherwise, they were marked (-), as shown in Table 6. The changes in the indicators before and after patent transfer are shown in Table 7 and 8.

Table 6: The Properties of the Technological Network.

Indicators	High/low	Mark	Properties
$TKS$	High	$S^+$	The peculiarity of the technologies, and the technological status in the network.
	low	$S^-$	
$TKR$	High	$R^+$	The overlap of the technologies between one company and others, and the number of cooperation opportunities with other companies.
	low	$R^-$	

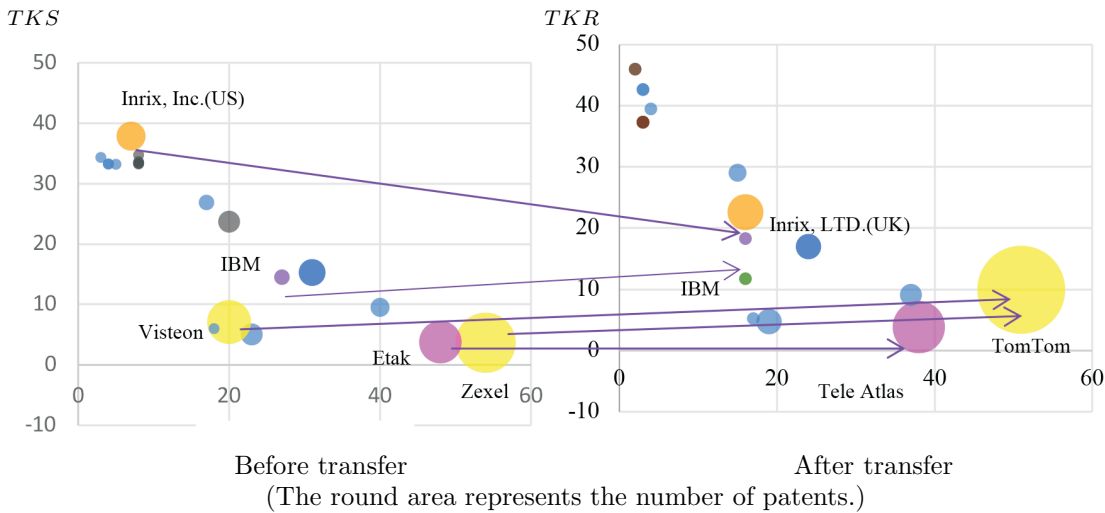


Figure 7: Knowledge position niche plot.

### Step 3: A Case Study for Technology Movement

Some patterns for technology transfer and the corresponding properties of the technological network were summarized by analyzing the properties of the technological net-



Table 7: Before transfer — codes for technological network properties.

Transfer Number	Companies (Before transfer)	<i>TKS</i>	<i>TKR</i>
M01A	IBM Corporation(US)	$S^+$	$R^-$
M01A	Applied Generics Limited(GB)	$S^+$	$R^+$
M01A	Visteon Technologies, Inc.(US)	$S^+$	$R^-$
M01A	Zexel Corporation Daihatsu-Nissan Ikebukuro(JP)	$S^+$	$R^-$
M01B	Sony Corporation(JP) — Etak, Inc.(US)	$S^-$	$R^-$
M01B	Poppen; Richard F.(US)— Smartt; Brian E.(US)— Dunn; Linnea A.(US)— Deroose; Frank J.(US)	$S^-$	$R^+$
M01B	Etak, Inc.(US)	$S^+$	$R^-$
M02	DeKock; Bruce W.(US)	$S^+$	$R^+$
M03	Luciani; Sergio(US)	$S^-$	$R^+$
M03	Wenking Corp.(CA)	$S^-$	$R^+$
M04	Inrix, Inc.(US)	$S^-$	$R^+$
M04	Infomove.COM, Inc.(US)	$S^+$	$R^-$
M05	Mytrafficnews.com, Inc.(US)	$S^-$	$R^-$
M05	Navteq North America, LLC(US)	$S^-$	$R^+$
M05	Traffic.com, Inc.(US)	$S^+$	$R^-$
M06	Trimble Navigation Limited(US)	$S^-$	$R^-$
M06	At Road, Inc.(US)	$S^+$	$R^-$
M07A	Mannesmann AG(DE)	$S^+$	$R^+$
M07B	Motorola Inc.(US)	$S^+$	$R^-$
M08	Daimler-Benz AG(DE)	$S^-$	$R^+$
M08	Decell, inc.(US)	$S^+$	$R^+$

work transfer and by collecting major acquisitions from the technological field and from public information of concerned companies.

- (1) Strengthening Foothold by Increasing Barriers (Transfer Number: M01A, M01B, M04, M08)

[M01A/B]: Tomtom (M01A) is a leading brand for satellite navigation systems. In order to strengthen its technological status in the navigation industry, it strategically acquired Applied Generics in 2006 and started developing the technology of real-time road conditions. One year later, it acquired Horizon Navigation Inc., a company with 18-years experience in producing in-vehicle navigation systems for cars; through this, it acquired 16 patents from Visteon and 30 patents from Zexel. In 2010, it acquired 1 IBM patent. Its technological network properties after acquisition were  $S^+$ ,  $R^-$ .

Table 8: After transfer — codes for technological network properties.

Transfer Number	Companies (After transfer)	$TKS$	$TKR$
M01A	IBM Corporation(US)	$S^+$	$R^-$
M01A	TomTom Global Assets B.V.	$S^+$	$R^-$
M01B	Tele Atlas North America CA	$S^+$	$R^-$
M01B	Sony Corporation(US)	$S^+$	$R^-$
M02	Traffic Information, LLC	$S^+$	$R^-$
M03	Strategical Design Federation W, INC.	$S^+$	$R^-$
M04	Inrix UK LTD.	$S^+$	$R^-$
M05	NAVTEQ B.V.	$S^+$	$R^+$
M06	Trimble Navigation Limited	$S^+$	$R^+$
M07A/B	Continental Automotive GMBH	$S^+$	$R^+$
M07B	CDC Propriete Intellectuelle	$S^-$	$R^-$
M07A	Motorola Inc.(US)	$S^+$	$R^-$
M07A	Agero Connected Service, INC.	$S^+$	$R^+$
M08	Ramsle Technology Group GMBH, LLC	$S^+$	$R^+$

The more unique it is, the lower the technological relevance is and the higher the technological barrier a company establishes.

[M04]: Inrix Inc., which was founded by former Microsoft employee, Bryan, in 2004, provides real-time traffic information and path prediction. It provides information for big manufacturers of smartphones and cars. Its technological status and abilities as an intermediary were insufficient in the ITS field before transfer (the properties are shown as  $S^-, R^+$ ). In 2011, Inrix Inc. acquired Integrated Transport Information Services along with one patent from Infomove, a patent with high values for technological status ( $S^+, R^-$ ). After the acquisition, its technological network properties were  $S^+, R^-$ .

(2) A Cash Cow for the NPE (Transfer Number: M02, M03)

[M02]: Traffic Information LLC in Texas of the United States is a patent-holding company. Patent licensing revenues are its main sources of income. In this case, the transferred patent enables phone users to receive real-time traffic information by setting up network traffic monitors and network transmission. The three inventors, Bruce Dekock, Kevin Russell, and Richard Qian, obtained the invention rights on August 31, 2004. Later, the invention rights were transferred to Traffic Information LLC on June 16, 2009. The patented real-time traffic information system covered a wide range of inventions. Traffic Information sued several famous companies like Volvo, Honda, HTC, Samsung, RIM, Yahoo, Google, Sony, and HP. For the technological network analysis, the aforesaid three patents had the properties of  $S^+, R^+$ .

The three patents cover a wide range of exclusive rights, and maintenance costs for the patents are not that expensive. Consequently, the acquisition of patents such as this serves as a cash cow for patent trolls.

[M03]: Companies fear patent infringement lawsuits; therefore, patent licensing alliances like Strategic Design Federation W Inc., emerged and thrived. For the case of M03, one patent for Luciani, Sergio (US) whose properties were marked as  $S^-$ ,  $R^+$  and one patent for Wenking Corp. (CA) whose properties were marked as  $S^-$ ,  $R^+$ . The  $TKS$  values were slightly lower than the corresponding averages which mean that the two patents have high technological relevance and wide exclusive rights, but the maintenance costs are relatively low. This makes them good targets for Strategic Design Federation W Inc., a company that profits from patent licensing.

- (3) Shortcuts for Marginal and New Entrants (Transfer Number: M05, M06, M07A, M07B)

[M05]: Navteq was a provider of Geographic Information System (GIS) data. It had a relatively low technological status in the technological network (its properties were marked as  $S^-$ ,  $R^+$ ). In November of 2006, Navteq announced the acquisition of Traffic.com Inc., a provider of real-time traffic information for Internet, phones and broadcast companies. Through this, it obtained two important patents (one from Mytrafficnews.com Inc) which greatly improved its technological network status. Its properties were now marked as  $S^+$ ,  $R^+$ .

[M06]: Trimble Navigation Limited focuses on the development and application of surveying and mapping technology. Its technological network parameters were relatively low with properties marked as  $S^-$ ,  $R^-$ . Trimble acquired Road Inc. in 2007 which greatly improved its status. Its properties changed into  $S^+$ ,  $R^+$ .

[M07A, M07B]: Mannesmann AG is the predecessor of Vodafone LSE. Its corporate activities in the area of telecommunications were very successful. It had approximately 439, 000, 000 users across the world. Mannesmann AG had four patents and it transferred them to Agero Connected Services Inc.; while the other two were transferred to Continental Automotive GMBH. In addition, Continental Automotive GMBH acquired another patent from Motorola Inc. After the acquisition, Mannesmann AG (Vodafone LSE) withdrew from the industry. Even though Motorola Inc. transferred two patents to other companies (one to Continental Automotive GMBH while the other to a patent holding company), it still holds a position in the ITS (its properties were marked as  $S^+$ ,  $R^-$ ). The new entrants, Agero Connected Services, Inc., and Continental Automotive GMBH, quickly joined the market through patent acquisitions (their properties were marked as  $S^+$ ,  $R^+$ ).

Having analyzed the changes in the technological positions of the companies in the field of Cloud and ITS before and after patent acquisitions, the implications for management are summarized as follows:

- (1) After patent transfer, more companies obtained high positions in the technological network and gained abundant resources (their properties were marked as  $S^+$ ,  $R^+$ ). On the other hand, more companies also attained low positions in the technological

network and had decreased resources (their properties were marked as  $S^-$ ,  $R^-$ ). This fact reveals that the strong become stronger while the weak become weaker after technological transfer.

(2) The manufacturers that strengthened their foothold by increasing barriers tend to have low values of  $TKR$  but very high values of  $TKS$ . This shows that these companies develop their own unique technologies by integrating patents. Through this, they remain in the dominant state in the technological field by lowering their chances of cooperating by other competitors.

(3) For patent trolls and patent licensing alliances, they acquire patents with high values for  $TKS$ , but they do not consider the value of  $TKR$  as a major factor in reducing costs, and in instituting proceedings and licensing extensively.

In order to obtain high positions in the technology industry and gain cooperation opportunities, marginal or new entrants of the technological field would need to acquire patents with high  $TKS$  and  $TKR$ .

#### 4. Conclusions and Further Research

Cloud computing and smart transportation systems fall onto the high-tech intensive industry. In this kind of industry, the product life cycle is very short while various technologies involved in product design, but there is a lot of competition in the market. In addition, the lawsuits are frequently filed in the industry. Not only do some involved parties make compensation, but also their product sales rights and market share are affected. Therefore, the development speed of innovative technologies and products, and the strategy of patent layouts have become the key factors that determine the sustainability of Cloud-based industry vendors. Moreover, the changes in the technological positions before and after patent transfer revealed three patent acquisition strategies namely: strengthening foothold by enhancing barriers, a cash cow for NPE, and a shortcut for peripheral and new entrants. This research uses the indicators of  $TKS$  and  $TKR$  to build a more complete model for corporate technology assessment. After the establishment of the model, through the analysis and verification of the intelligent transportation system industry, the technological positions before and after the company's acquisition of the patents shown in the technological coordinate map can provide insight into the company's strategic intentions.

The  $TKS$  value represents the independent research and development capability of a company, which means whether a company can develop unique or pioneering patented technologies. A high  $TKS$  value means that the patented technology owned by the company is more unique than other existing technologies in the market. If a patented technology is applied to a small-sized niche market or an emerging market, this patented technology is not widely cited by other companies. Therefore, its  $TKS$  value is relatively low. In addition, the  $TKS$  value also represents a relatively high technological position within the competitive environment of the same field.

- (1) High  $TKS$  values represent that companies have relatively good independent research and development capability, or a relatively high technological status. Companies with high independent research and development capability are more likely to develop unique or pioneering technologies. Thus, they are more likely to become pioneers in emerging markets or have exclusive niche markets. That is because they have a relatively good absorptive capacity, whether it is through the acquisition of specific technologies or independent research.
- (2) A low  $TKS$  value means that a company's independent research and development capability or its technological status is relatively low. When the company's independent research and development capability are low, it needs to acquire or develop new technologies through cooperation with outside organizations, patent acquisitions, or patent authorization. Therefore, its technological development is highly overlapping with other companies, and hence its technological status is also relatively low.

The  $TKR$  value represents the degree of technology redundancy between companies. When a patent is cited by other companies, or a company quotes others patents to a high degree, the technological redundancy between companies is high.

- (1) A high  $TKR$  value indicates that the company has a relatively good capability to expand its market. When the market shows potential, which in turn attracts other companies to cite the patent, the  $TKR$  values of the companies that cite this technology and whose technology is cited are both high. Unlike the companies with high  $TKR$  and  $TKS$  values, the ones with high  $TKR$  but relatively low  $TKS$  are able to exploit the market potential of patented technologies and cite them, despite their inability to possess relatively unique patented technologies. Therefore, they have a relatively high market development capability.
- (2) A low  $TKR$  value indicates that a company has a low ability to develop new markets, or that the technology which it possesses has no market potential or of little market value. When technology is of low market value or potential, there is a relatively low possibility that its patents will be frequently cited by other companies. Thus, it has a relatively low level of technological redundancy with other companies. As a result, its  $TKR$  value is low. In addition, when a company discovers new markets but they do not have sufficient resources to support its development of new markets, and its capability does not attract the cooperation of other companies, it will run into the predicament that it is unable to cite new patented technologies and develop unique technologies. Thus, its  $TKR$  value is relatively low.

It is hoped that the results of this study can serve as a reference for internal inspections and strategic planning in the future. However, this study only discusses some enterprises within the Cloud industry and does not explore all enterprises in the industry. Therefore, the research results are only applicable to the industry, and cannot be generalized and applied to other industries. The following topics are the ones that may be worth further study.

- (1) In this study, only the trajectories of corporate technological position movements are classified. In the future, the trajectories are expected to be more accurately classified based on centrality or means, hoping that the relative positions of the enterprises in the technological network can be accurately spotted.
- (2) In the future, the studied industrial category can be expanded and cross-examination can be carried out to generalize strategic implications that are applicable to a wider range of fields.
- (3) In future research, all companies within the industry of Cloud and smart transportation system can be discussed, and comprehensive analysis can be conducted. Also, technology grouping can be done to observe various dimensions, such as movement trends, movement barriers between groups, and the change of individual role positions within groups.
- (4) In the different technology life cycles, the industry enterprises need to adjust their competitive strategy, and their relative technological positions will change along with it. In this case, the problem that the enterprises may face in different technological life cycles within the industry and with different technological positions and corresponding strategies can also be explored.

### References

- [1] Breitzman, A. and Thomas, P. (2002). *Using patent citation analysis to target/value M&A Candidates*, Research Technology Management, Vol.45, 28-36.
- [2] Breschi, S. and Lissoni, F. (2005). Handbook of Quantitative Science and Technology Research, the Use of Publication and Patent Statistics in Studies of S&T Systems. (H. F. Moed, W. Glanzel & U. Schmoch Eds.). Netherlands: Springer.
- [3] Cantner, U. and Graf, H. (2006). *The network of innovators in Jena: An application of social network analysis*, Research Policy, Vol.35, 463-480.
- [4] Chen, S. J. and Lai, K.K. (2012). *Using the ego-centered technology network perspective to identify the most suitable commercialization partnership*, Journal of Management & Systems, Vol.19, 589-623.
- [5] Chen, S. J., Su, F.P., Lai, K. K., Yang, M. T. and Chang, P. C. (2013), *The patent information, strategic patent deployment thinking, and technology strategies of small and medium-sized enterprises*, Proceedings of the Portland International Center for Management of Engineering and Technology (PICMET 2013), California, USA, July 28-August 1, 48-61.
- [6] Ghoshal S. (1987). *Global strategy: An organizing framework*, Strategic Management Journal, Vol.8, 425-440.
- [7] Glover, F. and Laguna, M. (1993). Tabu Search in Modern Heuristic Techniques for Combinatorial Optimization, Oxford, UK: Blackwell Publishers.
- [8] Griliches, Z. (1990). *Patent statistics as economic indicators: A Survey*, Journal of Economic Literature, Vol.4, 1661-1707.
- [9] Gulati, R. (1995). *Social structure and alliance formation patterns: A longitudinal analysis*, Administrative Science Quarterly, Vol.40, 619-652.
- [10] Hagedoorn J. (2002). *Inter-firm R&D partnerships: an overview of major trends and patterns since 1960*, Research Policy. Vol.31, 477-492.
- [11] Hall, B. H., Jaffe, A. and Trajtenberg, M. (2005). *Market value and patent citations*, The RAND Journal of Economics, Vol.36, 16-38.
- [12] Hitt, M. A., Hoskisson, R. E., Johnson R. A. and Moesel, D. D. (1996). The Market for Corporate Control and Firm Innovation, The Academy of Management Journal, Vol.39, 1084-1119.
- [13] King, D. R., Slotegraaf, R. J. and Kesner, I. (2008). *Performance implications of firm resource interactions in the acquisition of R&D-intensive firms*, Organization science, Vol.19, 327-340.

- [14] Kumar, V., Lin, C. Y., Lai, K. K., Chang, Y. H. (2019). “*Computing redundancy in complementary and supplementary technologies using TLC indicators: A theoretical framework*”, Accepted at Portland International Conference on Management of Engineering & Technology (PICMET’ 19) held on August 25-29, 2019 in Portland, Oregon - USA.
- [15] Kumar, V., Lai, K. K., Chang, Y. H., Lin, C. Y. (2018a). “*Mapping technological trajectories for energy storage device through patent citation network*” . Ninth IEEE International Conference on Awareness Science and Technology (iCAST 2018) held at Fukuoka, Japan, Sept. 19-21, 2018, 56-61.
- [16] Kumar, V., Lai, Chen, H. C., Lin, C. Y., Lai, K. K., Chang, Y. H. (2018b). “*Technological evolution of thin-film solar cells through main path analysis*” . In Proceedings of the 2nd International Conference on E-Society, E-Education and E- Technology (ICSET 2018) held in Taipei, Taiwan, Aug. 13-15, 2018, 160-164.
- [17] Lai, K. K. and Wu, S. J. (2005). *Using the patent co-citation approach to establish a new patent classification system*, Information Processing and Management, Vol.41, 313-330.
- [18] Lai, K. K., Chen, S. J., Chang, Y. H., Yang, W. G. and Weng, C. S. (2014). Find the Right Transferee for Patents by Ego Patent Citation Network: Evidence from Kodak, ICE Conference, Bergamo, Italy.
- [19] Lizina, S., Leroyb, J., Delvennec, C., Dijkd, M., De Scheppera, E. and Van Passel, S. (2013). *A patent landscape analysis for organic photovoltaic solar cells: identifying the technology’s development phase*, Renewable Energy, Vol.57, 5-11.
- [20] Makri, M., Hitt, M. A. and Lane, P. J. (2010). *Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions*, Strategic Management Journal, Vol.31, 602-628.
- [21] Narin, F., Noma, E. and Perry, R. (1987). *Patents as indicators of corporate technological strength*, Research Policy, Vol.16, 143-155.
- [22] Park, Y. and Yoon, B. (2013). *Identifying potential partnership for open innovation by using bibliographic coupling and keyword vector mapping*, International Journal of Computer and Information Engineering, Vol.7, 206-211.
- [23] Podolny, J. M. and Stuart, T.E. (1995), *A role-based ecology of technological change*, American Journal of Sociology, Vol.100, 1224-1260.
- [24] Podolny, J. M., Stuart, T. E. and Hannan, M. T. (1996). *Networks, knowledge, and niches: competition in the worldwide semiconductor industry, 1984-1991*, American Journal of Sociology, Vol.102, 659-689.
- [25] Small, H. (1973). *Cocitation in the scientific literature: a new measure of the relationship between two documents*, Journal of the American Society for Information Science, Vol.24, 265-269.
- [26] Stuart, T. E. (1998). *Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry*, Administrative Science Quarterly, Vol.43, 668-698.
- [27] Stuart, T. E. and Podolny, J. M. (1996). *Local search and the evolution of technological capabilities*, Strategic Management Journal, Vol.17 (Special Issue: Evolutionary Perspectives on Strategy), 21-38.
- [28] Villalonga B. and McGahan AM. (2005). *The choice among acquisitions, alliances, and divestitures*, Strategic Management Journal, Vol.26, 1183-1208.
- [29] Von Wartburg, I., Teichert, T. and Rost, K. (2005). *Inventive progress measured by multi-stage patent citation analysis*, Research Policy, Vol.34, 1591-1607.
- [30] Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*, UK: Cambridge University Press.
- [31] Weng, C. S. and Lai, K. K. (2009). *On the technological isomorphism of insurance business method patents - the perspective of social network analysis*, Journal of Management, Vol.26, 485-506.
- [32] Wu, Shiao-Jun. (2003). Using patent co-citation analysis to establish patent classification support system- illustrated with foundry industry (Ph.D.), National Yunlin University of Science and Technology.
- [33] Yoon, B. and Park, Y. (2004). *A text-mining-based patent network: Analytical tool for high-technology trendf*, Journal of High Technology Management Research, Vol.15, 37-50.

Department of Management Sciences, Tamkang University, New Taipei City, Taiwan.

E-mail: chj@mail.tku.edu.tw

Major area(s): Marketing research topics, statistical application topics.

Department of Management Sciences, Tamkang University, New Taipei City, Taiwan.

E-mail: csc321@gmail.com (Corresponding Author)

Major area(s): Financial, statistical analysis, Patent analysis.

Department of Marketing and Logistics Management, Chaoyang University of Science and Technology, Taichung, Taiwan.

E-mail: yhchang1991@cyut.edu.tw

Major area(s): Marketing, Patent analysis, Business model.

Department of Business Administration, Chaoyang University of Technology, Taichung, Taiwan.

E-mail: vimaljss91@gmail.com

Major area(s): TQM, manufacturing strategy, supply chain, technological innovation management, and patent analysis.

Department of Business Administration, Chaoyang University of Technology, Taichung, Taiwan.

E-mail: jay750728@yahoo.com.tw

Major area(s): Technological innovation management, patent analysis, business model.

Department of Business Administration, Yunlin University of Science and Technology, Yunlin, Taiwan.

E-mail: iru71310@gmail.com

Major area(s): Management of technology, patent analysis, product design.

(Received December 2018; accepted June 2019)