Mapping the Evolution of Technology Network in the Field of Solar Energy Technology

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Abstract
This paper aims to map the evolution of technology network in the field of solar energy technology worldwide during 1971-2010 by using patent analysis and social network analysis. Results show that technology network of main component during 2001-2010 is much bigger than that of during 1971-1980, and the scale of each sub-network, especially the biggest sub-network during 2001-2010 is much larger than that of during 1971-1980. The nature of generic technology seems to be weaker during 2001-2010 than that of during 1971-1980 with the robustly growing of solar energy technology. Results in this paper might help technology managers and policy makers on decision making.

Introduction
Solar energy is considered a key source for the future for the entire world. As the cleanest, most abundant, renewable energy source available, solar energy is emerging rapidly, and is noticed by national governments last decades, especially in the post-crisis era. Solar energy technology is listed as a strategic and emerging field to develop with priority by many countries (Faiman, Raviv & al., 2007; Li, Zhang & al., 2007; Martins, Pereira & al., 2008; Munda & Russi, 2008; Fthenakis, Mason & al., 2009). The existing related studies on solar energy mainly focused on the following aspects: the technical, geographical, and economic feasibility for solar energy to supply the energy needs (Singh, Lund & al., 1983; Fthenakis, Mason & al., 2009); exploitation of solar energy (Siddiqi & Hein, 1977; Hayes, 1978; McCarney, 1981; Coldicutt & Williamson, 1992; Faiman, Raviv & al., 2007; Zaksek, Marsetic & al., 2007; Sharan, 2009); solar energy policy (Chakrabarti, 2002; Lamei, van der Zaag & al., 2008; Martins, Pereira & al., 2008; McEachern & Hanson, 2008); and solar energy education (Hasnain, Alawaji & al., 1998), & al.

With the robust developing of solar energy technology, how are solar energy technology network evolving? Related studies have not been found yet. This study aims to map the evolution of technology network by using patent analysis and social network analysis during 1971-2010. For being limited by the length of this paper, we choose two decades, i. e., 1971-1980 and 2001-2010, to analyze.

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Patent data are selected to analyze the evolution of solar energy technology network. For patent documents contain rich technical information related to intellectual property rights and important research results (Lawson, Kemp & al., 1996; Tseng, Lin & al., 2007; Magerman, Van Looy & al., 2010), and are usually considered the proper datasets in the analysis of technology developing.

This paper is organized as follows: Following this introduction, Section 2 introduces related studies on mapping technology network. Section 3 presents the dataset and methodology. Section 4 maps technology networks. Section 5 makes conclusions and discusses the findings.

**Related studies on mapping technology network**

Social network analysis (SNA) is not a formal theory in sociology but rather a strategy for investigating social networks (Otte & Rousseau, 2002). Since SNA has developed as a specialty in parallel with scientometrics in the 1970s (Yan & Ding, 2009), SNA has widely applied in scientometrics, such as scientific collaboration analysis (Kretschmer & Aguillo, 2004; Wagner & Leydesdorff, 2005; Hou, Kretschmer & al., 2008; Leydesdorff & Wagner, 2008), co-citation analysis (Wouters & Leydesdorff, 1994; Otte & Rousseau, 2002; Marion, Garfield & al., 2003; Johnson & Oppenheim, 2007; Chen, Chen & al., 2009; Leydesdorff, 2009; Wang, Zhang & al., 2011), and co-occurrence analysis (Small, 1973; Morris, 2001; Leydesdorff & Vaughan, 2006; Leydesdorff, 2007; Waltman & van Eck, 2007; Jeong & Kim, 2010).

However, only a few studies on technology network by using SNA have been found. The existing studies focus on the influence of business strategies on technological network activities (Gemunden & Heydebreck, 1995), high-technology network in northern Finland (Jauhiainen, 2006), the role of transnational corporations in the Chinese science and technology network (Hennemann, 2011), and global technology analysis (Nam & Barnett, 2011). Studies on technology network in a certain technology field, such as solar energy technology field, have not been found yet, nor have we found studies on mapping the evolution of solar technology network.

**Data and methodology**

*Data in the study*

*Data retrieval*

The data in this study is retrieved from *Derwent Innovations Index* (abbr. as *DII* below). *DII* is one of the most comprehensive databases collecting patent documents in the world, begun in 1963 and currently published by *Thomson Reuters*. *DII* includes three parts: Chemistry, Engineering and Electric & Electronics. Every week 25,000 patent documents published by more than 40 patent offices and 45,000 patent citation documents from 6 important copyright offices are input into *DII*. The publication dates are used in this study. Because one patent family include one basic patent and one or more equivalent patent(s), the number of patents in this study is of the basic patent, not all applications. The basic patent publication date is definite.

Every single bibliographic patent record in *DII* is assigned with three different classification standards, which are International Patent Classification Code (IPC), Derwent Class Code (DC), and Derwent Manual Code (MC). The authors adopt the definition of solar energy technology with IPC provided by *World Intellectual Property Organization* (abbr. as *WIPO*) (WIPO 2011), and time span=1971-2010. The data was retrieved and downloaded on October 20, 2011. There are 153,650 solar energy patent filings during 1971-2010, and Figure 1 demonstrates the growing trend in patent filings of solar energy worldwide.
**Data processing**

We use the data format conversion function of CiteSpace (Chen, 2006) to convert the patent publications downloaded from DII into the Web of Science export format, for most of the data-processing research software such as CiteSpace, Bibexcel, being designed originally to process data with the format of Web of Science (Chen, 2010). Bibexcel (Persson, 2012) and Ucinet (Masu, Katagiri & al., 2008) are employed to analyze the converted patent data.

*Mapping technology network*

*Co-classification matrix*

DC, i. e.: Derwent Class Code is chosen as patent classification in this study. According to the trainer of DII named Zheng Wu, DC is a kind of classification with details indicated by more than 1,000 technicians of Thomson Reuters, and DC is considered to be quite accurate in patent classification (Wu, 2011). Moreover, DC patent classification is operated by a same grade standard, i. e., each DC patent classification is composed of one capital letter plus two digits, such as A81, U12, Q75, S03. Whereas both IPC and MC operates a hierarchical system patent classification, namely, different grades of patent classifications could be involved in a same patent record, such as S03-E03, S03-E03B2, S03-E03B2C1 which are included in a same patent record in MC, and this situation is easy to confuse readers. Seriously speaking, this hierarchical system of patent classification is improper to be used in the similar studies.

A patent filing often involves two or more technology classifications. In DII, a patent record usually has several DCs, and so we can get technology co-classification matrix as the following, and the italics on the main diagonal represent the frequency of a fixed DC, such as 169 is the frequency of A14, and so on.
Table 1. Technology co-classification matrix (part).

<table>
<thead>
<tr>
<th></th>
<th>A14</th>
<th>A26</th>
<th>A85</th>
<th>A88</th>
<th>A89</th>
<th></th>
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<td>A14</td>
<td>169</td>
<td>29</td>
<td>127</td>
<td>6</td>
<td>51</td>
<td></td>
</tr>
<tr>
<td>A26</td>
<td>29</td>
<td>158</td>
<td>123</td>
<td>1</td>
<td>59</td>
<td></td>
</tr>
<tr>
<td>A85</td>
<td>127</td>
<td>123</td>
<td>2680</td>
<td>11</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>A88</td>
<td>6</td>
<td>1</td>
<td>11</td>
<td>555</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>A89</td>
<td>51</td>
<td>59</td>
<td>72</td>
<td>4</td>
<td>731</td>
<td></td>
</tr>
</tbody>
</table>

**The normalized matrix by Jaccard Index**

The Jaccard index is used to normalize the co-classification matrix in Table 1. Leydesdorff (Leydesdorff, 2008) debated that in co-citation analysis or co-occurrence analysis, Jaccard index should be used. He proposed that unlike Salton's cosine and the Pearson correlation, the Jaccard index abstracts from the shape of the distributions and focuses only on the intersection and the sum of the two sets. Since the correlations in the co-occurrence matrix may be spurious, this property of the Jaccard index could be considered as an advantage in this case. According to the Formula provided by Leydesdorff (Leydesdorff 2008), we can use Formula (1) to show the computing method of Jaccard index:

\[
S(i, j) = \frac{\text{cooc}(i, j)}{\text{occ}(i) + \text{occ}(j) - \text{cooc}(i, j)}
\]

Where \(S(i, j)\) represents the co-classification strength of technology classification \(i\) and \(j\), which means that \(S(i, j)\) is Jaccard index. \(\text{cooc}(i, j)\) represents co-occurrence times of \(i\) and \(j\), \(\text{occ}(i)\) and \(\text{occ}(j)\) represents occurrence frequency of \(i\) and \(j\), respectively.

The value of Jaccard index ranges from 0~1, the higher the value is, the more similar is between \(i\) and \(j\).

**Technology network and Girvan-Newman algorithm**

After getting technology co-classification normalized matrix of Jaccard index, we transfer the normalized matrix into \((0, 1)\) matrix and adjust threshold to avoid heavy overlap to get clearly and ideally technology network.

The Girvan-Newman algorithm is used to detect communities in technology network (Girvan & Newman, 2002). Girvan and Newman highlighted a property that is found in many networks, the property of community structure, in which network nodes are joined together in tightly knit groups, between which there are only looser connections. They proposed a method for detecting such communities, built around the idea of using centrality indices to find community boundaries. And they tested their method on computer-generated and real-world graphs whose community structure was already known, and found that the method detects this known structure with high sensitivity and reliability.

**Analysis and results**

*Stage 1: 1971-1980*

Analyzing DC of 2,387 solar energy patents during 1971-1980 by using the hypertext software of Bibexcel (Persson, 2012), we get the co-classification matrix of technology classifications. And
then Jaccard index is used to get the normalized matrix. *Netdraw* tool of *Ucinet* is applied to draw the technology network. By adjusting the threshold continuously, we get the clear and ideal main component technology network (Figure 2).

![Figure 2. Technology network of solar energy during 1971-1980, threshold=0.07.](image)

The Girvan–Newman algorithm is used to identify sub-networks in Figure 2. The biggest sub-network is concerning Photochemistry Conversion and Thermoelectric Conversion; followed by sub-networks such as Optical Equipment, Heat Engines, Shaping Metal, LED Lighting, Photosensitive Compositions; and sub-networks like Heat Transfer and Drying, Heterocyclics-Solar Cells and Solar Heating are comparatively smaller ones during 1971-1980.

**Stage 1: 2001-2010**

By using the same method and choose DCs with high frequency, we get the main component technology network of Stage 2 (Figure 3).

![Figure 3. Technology network of solar energy during 2001-2010, threshold=0.03.](image)

The biggest sub-network is Solar energy power generation & Solar photovoltaic cells, followed by other comparatively bigger sub-networks, such as sub-network of Solar Water Heater & Layered
Conclusions and discussions

Using patent data in the field of solar energy downloaded from one of the most comprehensive world patent databases Derwent Innovation Index (DII), we draw solar energy technology networks by choosing two decades, 1971-1980 and 2001-2010, and have an overview of the evolution of solar energy technology networks.

Technology network of main component during 2001-2010 is much bigger than that of during 1971-1980, and the scale of each sub-network, especially the biggest sub-network during 2001-2010 is much larger than that of during 1971-1980. During 1971-1980, the technology network is comparatively looser, and the scale of each sub-network is smaller; however, during 2001-2010, the technology network is much tighter, and the scale of sub-network is much bigger. This trend indicates that solar energy technology are focusing on several main areas, such as Solar energy power generation & Solar photovoltaic cells, Solar Water Heater & Layered Products and Solar Power Heating & Refrigeration. The nature of generic technology seems to be weaker during 2001-2010 than that of during 1971-1980 with the robustly growing of solar energy technology.

The result of the analysis are still in a macro-level, and for being limited by the length of this paper, we only choose two decades to analyze. A more in dept and comprehensive analysis by using detailed classification codes will be tried later.

Findings in this study will benefit technology managers and policy makers in the field of solar energy technology. We will pay close attention to the evolution of technology network in the field of solar energy technology in the future.

References and Citations


