# PREDICTING TECHNICAL VALUE OF TECHNOLOGIES THROUGH THEIR KNOWLEDGE STRUCTURE

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**Abstract**


This thesis tests the hypothesis that the characteristics displayed by the knowledge structure of a high technical value invention is different from that of a low technical value invention. The knowledge structure represents the relationship of the invention with all the prior knowledge upon which it is based. This structure crystalizes at the inception of the invention making it ideal for evaluating new inventions.

More specifically, this research investigates two characteristics of the knowledge structure: knowledge accumulation and knowledge appropriation. Knowledge accumulation is defined as the collective body of knowledge, know-how and experiences gathered in a sector over time that have contributed to the creation of the invention. A higher degree of accumulated knowledge is more likely to be associated with high technical value inventions. Knowledge appropriation describes absorption of knowledge in the creation of the invention. From a knowledge structure perspective, knowledge absorption is observed by the emergence of edges that connect knowledge elements together. The robustness of this emergent knowledge structure is thus an indicator of the amount of knowledge appropriated by the invention. This research introduces a new metric for the measurement of knowledge accumulation and presents structural robustness as an indicator of knowledge appropriation. Knowledge accumulation and knowledge appropriation are tested as characteristics associated with knowledge structures and are hypothesized to be positively correlated with the technical value of the invention.

This research tests the hypotheses by examining the citation networks of patents in four sectors: thin film photovoltaics, inductive vibration energy harvesting, piezoelectric energy harvesting, and carbon nanotubes. In total 152 base inventions and over 4000 patents are investigated. This research shows that knowledge accumulation is a significant predictor of the technical value of an invention. This research also shows that high value inventions show a higher level of knowledge appropriation. The results demonstrate that the characteristics displayed by the knowledge structure are better able to explain the technical value of inventions compared to techniques demonstrated by other studies.

**Statement of originality**

This is to certify that, to the best of my knowledge, the content of this thesis is my own work.

This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Praveena Chandra
September 2018

**Thesis authorship attribution**

This thesis contains material published or submitted for publication, based on the work presented in the thesis, for which I am the main author. This material is distributed throughout all chapters.

**Conference Papers**

- Chandra, P., & Dong, A. (2015). *Knowledge accumulation and value of inventions*. 2015 Portland International Conference on Management of Engineering and Technology (PICMET), Portland, OR. doi: 10.1109/PICMET.2015.7273056
- Chandra, P., & Dong, A. (2015). *Predicting technical viability of inventions*. 2015 IEEE International Conference on Engineering, Technology and Innovation/ International Technology Management Conference (ICE/ITMC), Belfast. doi: 10.1109/ICE.2015.7438654

**Journal Articles**

- Chandra, P., & Dong, A. (2018). The relation between knowledge accumulation and technical value in interdisciplinary technologies. *Technological Forecasting and Social Change, 128*, 235-244. doi: 10.1016/j.techfore.2017.12.006

As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

Andy Dong
September 2018

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A minor part was also played by a few gallons of coffee, countless packets of paracetamol and one dress size, all of which were sacrificed in the making of this thesis!

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**List of abbreviations and acronyms**

| | |
|---|---|
| ASPL | Average shortest path length |
| CNT | Carbon nanotube |
| CPC | Cooperative patent classification |
| DNA | Deoxyribonucleic acid |
| DSSC | Dye sensitized solar cells |
| EPO | European Patent Office |
| FBS | Function-Behaviour-Structure |
| INPADOC | International patent documentation |
| IPC | International patent classification |
| IV | Inductive vibration energy harvesting |
| KA | Knowledge accumulation |
| NC | Node connectivity |
| OLED | Organic light emitting diode |
| PAIR | Patent application information retrieval |
| PZ | Piezoelectric energy harvesting |
| RC | Robustness coefficient |
| RFID | Radio-frequency identification |
| SNA | Social network analysis |
| TF | Technology forecasting |
| TLC | Technology life cycle |
| TRIZ | *Teoriya Resheniya Izobretatelskikh Zadatch* (Theory of inventive problem solving) |
| TRL | Technology readiness level |
| US | United States of America |
| USPC | United States patent classification |
| USPTO | United States Patent and Trademark Office |
| WIPO | World Intellectual Property Organization |

# 1 INTRODUCTION

## 1.1 Background

***Case 1:*** In 2001 Konarka Technologies Inc. was founded in Lowell Massachusetts USA as a spin-off from University of Massachusetts Lowell. The main product of Konarka was dye-sensitized solar cells (DSSC). DSSC's are third generation solar cells that have their foundation in photochemistry rather than solid-state physics. In these solar cells an electron is released from a light-sensitive dye when exposed to sunlight. This electron is then transported to the electrodes with the help of nano-particles, thus generating electricity. Studies highlighted, with caution, the advantages and attractiveness of this technology (McConnell, 2002; Roper et al., 2011). Due to the promising aspects of the technology, Konarka received over $190 million in private capital and government grants over the next ten years (Choe et al., 2013). The company's products however failed to reach the market and eventually the company filed for bankruptcy in 2012. One of the factors for the failure of Konarka's products was believed to be lack of maturity of the technology (Kirsner, 2012).

***Case 2:*** In late 2000's, *Jatropha curcas* came to be known as the next big solution to oil problems. It was considered the best candidate for biodiesel production due to the ease with which it could be cultivated. This led to large-scale investments in Jatropha plantations and biodiesel production technology in India, China, Tanzania, and many other parts of the world. Many oil giants such as British Petroleum planned major investments in the cultivation of this plant (Milmo, 2015). However, challenges in blending technologies and epigenetic issues were later recognized (Kant & Wu, 2011; Kumar et al., 2012). This eventually led to pullback in investments in the plantations.

Many such examples exist for which the lack of technical viability has resulted in non-performance of an invention on a commercial scale. While the market for the technology might seem appealing because of what the invention promises to do, the commercialization was hindered due to challenges in its technical viability. Geels and Smit (2000) note that such grandiose picturization of the technology is "… resulting from ignorance and short-sightedness of forecasters or futurists, lacking insights from technology studies and using too simplistic assumptions about the impact of technology".

The maturity of a technology indicates that the knowledge underlying it has reached a point where the knowledge is sufficient to solve the technological challenges present in the sector. Thus, the implementation of a technology into products is feasible only when its knowledge has reached maturity (Beierlein et al., 2015; McNamee & Ledley, 2013; McNamee & Ledley, 2012). Investors search for inventions that have a strong potential in the market to ensure a good return on their investment. Investing in patented inventions is a practical approach since, for an invention to be patentable, it should be industrially realizable[1]. However, the fact remains that being patented does not ensure that the invention will "work". Sichelman's (2010) study suggests that many patents remain uncommercialized because the technology is often under-developed, thus making them unsuitable for industrial application. While on one hand this points to the existing holes in the patenting system[2], on the other hand it highlights the need for better technology assessment techniques.

## 1.2 Current Challenges

Technological assessment is carried out to determine whether the technology introduced by an invention is mature enough to perform the functions that it is meant to at a commercial scale. This is the first step in the drafting of the commercialization plans of an invention. Accurate analysis at this stage is vital because unforeseen complexities in the technology often delay the development or in some cases lead to the abandonment of the commercialization itself. Such delays and abandonments result in wasted resources and funds. Moreover, an invention with mature technology would hold a higher technical value than an invention whose technology has not yet reached maturity. Therefore, being able to identify, at an early stage, inventions with sufficient technical viability to be implemented in a product helps in better management of the commercialization process and making better investment decisions.

A study by Farrukh et al. (2009) on technology evaluation practises in industries revealed that techniques for assessing a technology at an early stage primarily involved discussions between key personnel, experience of the board, gut feeling, or informal tools based on projections. This study was based on interviews with key personnel in the UK's pharmaceutical, aerospace and telecommunications industries and was conducted to develop a time-based view of technology valuation. In another study by Cooper et al. (2001), the industry practices in portfolio management for new product development were revealed. The aim of the study was to understand the process for decisions to continue research on a certain new product. The authors describe portfolio management as a dynamic decision process whereby a business's list of active products and R&D projects is constantly updated and revised. The study concluded that the decisions on whether or not to pursue a project predominantly depended on the financial methods. Very few businesses used the "probability of technical success" combined with financial models for making decisions and some still relied on "intuition and experience". This study however does not mention how "probability of technical success" was deduced by these organizations.

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[1] In some jurisdictions such as Europe and Japan, industrial applicability is a requirement for patentability.

[2] Seymore explains some of the reasons why inventions of questionable quality may sometimes be granted a patent (Seymore, 2013).

Though the industry practice primarily seems to rely on intuition in assessing technical value, research in technology forecasting suggests a number of qualitative and quantitative techniques. Qualitative techniques such as Delphi method and Technology Readiness Levels primarily rely on expert opinions. The underlying assumption behind seeking an experts' opinion is that the expert has been working in the domain long enough to understand the advances and shortcomings of the technology. Hence the expert should have a good understanding of whether or not the technology has reached maturity. However, expert opinions are known to be subject to bias. Research by Tetlock and Gardner (2015) shows that proficiency in a field doesn't necessarily make one a better forecaster. Experts often suffer from "over-confidence" and tend to overlook or underestimate the technical shortcomings. This bias may be minimised by using a panel of experts (or a crowd of experts) instead of a single expert. However, such surveys require resources in terms of money, time and personnel, which may not be feasible for all technology managers, and the possible disclosure of proprietary information, which is impractical. Limitations in expert opinions and studies based on expert opinions are well documented (Powell, 2003; Rowe & Wright, 1999).

The quantitative techniques such as those based on technology life cycle or bibliometrics are not predictive in nature. Though these techniques are capable of identifying valuable inventions, they can only do so at a later stage of the life of the invention. By this time, the value of the invention is already apparent through its performance.

## 1.3 Potential Solution

One of the angles that has not received much attention is the assessment of the technical value of an invention from the perspective of its knowledge structure. The architecture of an invention is composed of multiple layers of base and complementary technologies. Furthermore, these technologies are a result of various knowledge elements interacting together. Thus, the knowledge structure of an invention is composed of a network of knowledge elements that are connected to each other due to the knowledge that they share. These knowledge elements are the prior knowledge that have led to solutions to various technical problems in the sector and eventually to the conception of the invention. In this structure, failure of one knowledge element could result in the failure of the invention. Thus, one needs to look at the maturity of every technology in the knowledge structure while assessing the overall technical value of the invention.

One of the ways to observe the knowledge structure of inventions is through patent data. Patents are legal documents that grant the inventor the right to exclude others from using, making or selling their invention in return of disclosing the technical details of the invention. A patent document has a wealth of information, which can be used to understand the technical aspects of the invention and its legal implications. Many studies have used patent citation networks to explore the knowledge background of technologies (Bosworth, 2004; Curran & Leker, 2011; von Wartburg et al., 2005). Thus, patent citation networks may provide an ideal dataset for exploring the knowledge structure of inventions and evaluating their technical value.

This dissertation aims to assess the knowledge structure of inventions and its influence on the technical value of inventions. In doing so, this dissertation addresses two sub-questions: (1) What characteristics of the knowledge structure might indicate the technical value of the invention and (2) What metrics can be used to observe these structural characteristics? The technical value of an invention indicates its likelihood to be implemented in products and its importance to the implementation of subsequent inventions. This dissertation proposes techniques based on the knowledge structure to assess the technical value of an invention at an early stage of its life.

More specifically I explore two characteristics of the knowledge structure: knowledge accumulation and knowledge appropriation. Knowledge accumulation may be defined as the collective body of knowledge, know-how, and experiences gathered in a sector over time that have provided the foundation for the invention. Studies have shown that knowledge accumulation is indicative of growth in organizations and also in industries on the whole. Knowledge accumulation has also been associated with technological maturity in drug development research (Beierlein et al., 2015). Thus, a higher degree of accumulated knowledge is more likely to be associated with high technical value inventions. Knowledge appropriation indicates the knowledge absorbed from the sector in the creation of the invention. The knowledge network of a technological sector takes shape over time and provides solutions to various technological problems in the sector. This is achieved largely by the knowledge spillovers created in the sector through active research. A spillover effect is seen when an inventor benefits from the knowledge generated by another inventor. Therefore, when an inventor bases an invention on a prior knowledge, the inventor benefits indirectly from knowledge produced by a wider segment of the sector. From a knowledge structure perspective, knowledge absorption is observed by the emergence of edges that connect knowledge elements together. In a well-connected sector, the inventor would be able to appropriate a higher quantity of knowledge from the sector as compared to a sector with fewer knowledge spillovers. I apply the concepts of knowledge accumulation and knowledge appropriation to predict the technical value of inventions.

## 1.4 Contributions

Through this dissertation I make the following contributions to the field of technological forecasting:

1. I make a methodological contribution to technical value analysis based upon the evaluation of the knowledge structure of inventions.
2. I introduce a conceptual advance by presenting new two characteristics of knowledge structures, knowledge accumulation and knowledge appropriation, which have the potential to predict the technical value of inventions.

3. I introduce a new metric for knowledge accumulation and show that it is an indicator of the technical value of inventions.
4. I demonstrate that the concept of network robustness can be used to observe knowledge appropriation in inventions.
5. I demonstrate that the technical value of inventions is positively influenced by the knowledge accumulation and knowledge appropriation dimensions of knowledge structures.

## 1.5 Dissertation Structure

This dissertation is divided into 9 chapters. In Chapter 2, I present a review of literature on technology valuation studies. More specifically I review studies that attempt to evaluate the technical value of inventions through patent data. In Chapter 3, I explain the emergence of knowledge structures and their connection to the technical value of patents. Based upon available evidence, I present my arguments that lead toward my hypotheses. In Chapter 4, I discuss patent citation networks, which form the basis of knowledge structures in this thesis. In Chapter 5, I discuss the characteristics of a knowledge structure that could potentially be the technical value indicators. In this chapter I introduce knowledge accumulation and knowledge appropriation as technical value indicators. I elaborate how knowledge appropriation may be measured through the robustness of the knowledge structure. Chapter 6 provides details on the various methodologies used in data collection, patent citation network construction and analytical techniques used in this thesis. In Chapter 7, I present the details on the sectors and the data used in this research. To test my hypothesis, I use patent data from four sectors: thin-film photovoltaics, inductive vibration energy harvesting, piezoelectric energy harvesting, and carbon nanotubes. In Chapter 8, I explain the results and discuss their implications. I draw my conclusions in Chapter 9 and suggest directions for future research.

# 2 LITERATURE REVIEW

## 2.1 Introduction

The desire to know what the future holds has given rise to forecasting techniques of various kinds. Knowing what could happen helps us better prepare for the consequences or even change the outcome. For example, weather forecasts help us plan our out-door activities for the day. Market forecasts inform us of the possible movements in the stock exchange, thus enabling us to make investment decisions wisely.

“Technology forecasting is the process of using logical, reproducible methods to predict in quantifiable terms the direction, character, rate, implications and impacts of technological advance” (Vanston, 1977). Vanston (1977) argues that the nature of technical advance is strongly influenced by the needs and desires of the society, which makes technological forecasting a complex task. Thus, while a forecast cannot provide foolproof answers to management questions, it can predict the rate and direction of progress in a given technical area. However, today technology forecasting has come to encompass techniques that answer a wide range of questions that can apply to a specific invention, organization or a country on the whole. On a country level, technology forecasting (TF) takes the form of foresight programs, which provide guidelines to shape the national technology growth policies. Here, the purpose of TF is to identify technology sectors that promise growth and promote economy of the country (Beumer & Bhattacharya, 2013; Martin & Johnston, 1999). On an organizational level, TF answers questions that decide the growth path of the organization. In this environment, TF is employed for identifying competitive technologies, process improvements, new product introductions, emerging technologies or technology enhanced services (Bardsley, 2004; Barker & Smith, 1995). TF helps organizations plan and strategize for emerging technologies. Information from the forecasts helps the organization to prioritize their R&D activities. For managers, the forecasts provide inputs required for planning new product development or making strategic decisions such as collaborations, joint ventures, mergers etc. On a specific invention level, TF takes the form of technology evaluation. Being able to successfully predict the future impact of a specific invention translates to efficient resource allocation in R&D departments, higher return on investment for the investors, and more focussed planning for the managers.

My research question relates to technology evaluation. Managers employ technology evaluation techniques to assess whether an invention could contribute towards the growth plan of the organization. Out of a range of available technologies, they try to choose the one with highest value. The value of an invention may be defined in terms of its success in being implemented into a product, its role in the building of subsequent technologies, or the commercial returns it generates. In this chapter I first review some of the methodologies used in the evaluation of inventions. I then further investigate the literature of patent analysis-based methodologies since my research contributes to this subject.

## 2.2 Technology Evaluation Techniques

The value of an invention consists of two parts: its technical value and its commercial value. The technical value describes the importance of the invention in being implemented into products and/or subsequent inventions while the commercial value describes the financial returns it generates. The commercial value is highly dependent on the technical value. An invention with a high technical value may or may not have a commercial value due to market conditions or other socio-economic factors. However, an invention without technical value will not have any commercial importance. Hence, commercial value is inconceivable without technical value. It is therefore, important that the technical value of the invention is accurately recognized. Failure to do so may affect the commercial gains anticipated from the invention. For examples, Hagelin (2002) states that when evaluating an invention through the income method[3], if the technical value of the invention is unknown (new or unproven technology), the risk adjustment to net income could be as high as 50-70%. This implies that in the absence of robust technological evaluation procedures, an invention with new technology will be valued low even if the technology later proves to be valuable. While this may turn out to be beneficial for the investor, the same cannot be said for the inventor (or the owner of the invention). On the other hand, if the new technology indeed were unable to prove itself, it would lead to a loss for the investor, which could have been avoided in the first place. Thus, understanding the technical value is an important step in the drawing of the development plans of an invention and essential to its commercial value.

Technological maturity is an important contributor to the technical value of the invention. As per the description of technology life cycle, a technology can be marked as mature when the knowledge underlying the technology is successful in solving most of the problems addressed in the domain and can be implemented in products or process. Technology management studies already highlight the importance of technological maturity in various processes related to an organization (Cooper et al., 2001). For an organization that is adopting or investing in a new technology, ensuring that the maturity level of the technology is in line with the business plan is vital. For example, it has been observed that nascent technologies often do not produce successful products (Beierlein et al., 2015; McNamee & Ledley, 2013). Thus, investing in an early stage technology with the intention of implementing it into products in the near future will most likely result in a failure. On the other hand, investing in a technology that has long since passed its maturity point will increase the probability of being successfully implemented in a product. However, it might also mean that other competitive technologies exist which may have been a better choice. Therefore, understanding the technological

[3] Inventions, which are the intellectual assets of an organization, are often evaluated using various financial evaluation techniques. One such technique is the income model. This method values an asset based upon the present value of the net future income stream expected to be received over the life of the asset. See Hagelin (2002) for details.

maturity of the invention plays an important part in the accurate evaluation of the invention, as highly mature technologies often lead to high technical value.

The different techniques demonstrated in the literature for assessing technical value may be divided into two categories: Qualitative and Quantitative methods (Figure 2-1). The qualitative techniques assess an invention based on the first-hand information of the performance of the technology. The quantitative methods associate the value of the invention with certain parameters of the technology. These techniques are based on mathematical or statistical models. In the following sections, I review some of these techniques.

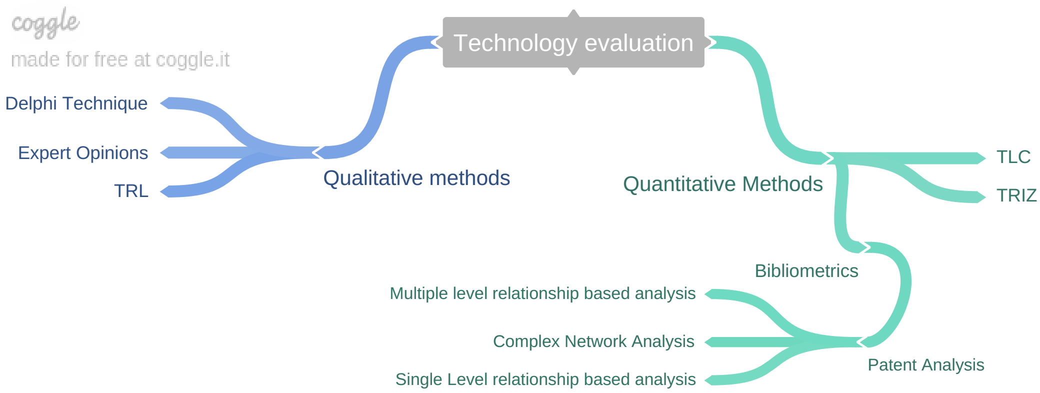



**Figure 2-1: Technological evaluation techniques**

### 2.2.1 Expert Opinions

Seeking expert opinion on the technical potential of an invention is the most commonly adopted technology evaluation technique. An expert of the field is expected to be well versed with the progress in the sector and the current challenges. Hence the expert should have an informed understanding of whether the solutions presented by the technology in an invention are robust enough thus, providing an estimation of its value. Opinions can be taken either from a single expert or a group of experts. For example, Albert et al. (2015) used the opinion of "crowd" as a measure of technical value. This research used blogs as its data and searched for specific terms related to the technology life cycle as indicator of maturity. Expert opinions however are subject to bias. Such a bias may be a result of personal beliefs or prior experiences. Also, employing the opinion of "crowd" may not be practical in case of new inventions, as this would necessitate disclosure of confidential information.

### 2.2.2 Delphi Technique

To minimize the risk of opinion bias, the Delphi technique can be employed to evaluate a technology. In this technique a panel of experts are asked a series of questions in two or more rounds. After each round, a facilitator provides to the panel an anonymous summary of the opinions expressed by the experts along with the reason for their judgement. The experts are then encouraged to revise their opinion in light of the responses provided by other experts. Thus, after several rounds, the opinions start to converge, leading to a more or less unified judgement. For example, based on a Delphi-type study, Islam and Brousseau (2014) created a multi-staged method for assessing the technology maturity of micro and nanotechnologies. In their study, the technology maturity scale and defining characteristics were decided based on discussions between academics and senior professionals.

After a review of studies on Delphi technique, Powell (2003) notes that this method may be subject to methodological weakness such as lack of clarity as to how consensus is defined. Conducting a Delphi survey requires resources in terms of money, time and personnel. Hence, this technique may not be feasible for all technology managers.

### 2.2.3 Technology Readiness Level (TRL)

Technology Readiness Level is a measurement system to assess the maturity level of a technology. There are 9 levels in this measure with 1 indicating the beginning of scientific research in the area and 9 indicating actual application of the technology. NASA first introduced this scale to evaluate the technology readiness of its various space mission programs. This was later adopted by other organizations. Studies such as the one by Rybicka et al. (2016) employed TRL in assessing technological maturity. When using TRL to assess a technology, the research project is assessed for its maturity level based on the pre-set milestones under each phase. For example, technology feasibility is achieved if the new idea is shown to work. The proof of concept stage is considered to have been achieved if the technology demonstrates the production of small number of components. Thus, the maturity of the technology is decided based on its ability to produce the results set for that specific maturity level. There is an underlying assumption that research projects naturally proceed to the next stage given enough time and/or work has been spent on the technology. However, it is known that many technologies that work at the proof-of-concept stage fail when scaled-up. For example, Scott et al. (2010) lists some of the technical and engineering challenges in the scaling up of algal biodiesel production. Mukherjee and Ray (1999) described the existing design of photocatalytic reactor as a limiting factor in the scaling up of semiconductor photocatalysis for water treatment. Similarly Rosner and Wagner (2012) observed scale-up effects in photobiological hydrogen production from small scale to large scale. A possible reason for failure in detecting the scale-up issues at an earlier stage is that often the maturity of the core technology of the invention is considered in isolation. In other words, the role of the external factors such as design limitations, material choices, or supporting technologies is ignored. Thus, while the main technology may work, the whole invention fails due to challenges in a supporting technology. The significance of these external factors is magnified when the technology is scaled up.

A study by Tomaschek et al. (2016) revealed that the implementation of TRL faces 15 distinct challenges that can be grouped into 3 categories: product and system complexity related, process and organizational view related, and assessment validity related. This study indicates that this system in its original form is not sufficient for assessing the maturity of technologies in complex system engineering. It is also argued that individual industries would need to customise and develop their own TRL levels.

### 2.2.4 Technology life cycle (TLC)

Literature on technology life cycle describes technologies as going through a typical "S" (Figure 2-2) curve during their lifetime (Christensen, 1992a, 1992b). The horizontal axis of this curve represents time and the vertical axis indicates the developments in the technological sector. This life cycle starts with the introduction of the technology. At this emerging stage, the technology has low integration in products or processes. In the growth stage, there are more competitive technologies; however, all the challenges of the sector do not yet have a solution for the technology to be implemented in a product or process. In the maturity stage key technologies emerge and so do products and processes. Eventually the technology loses its competitive impact and becomes a base technology, which may be replaced. Studies based on TLC primarily try to locate the current position of the technology within the "S" curve. Beierlein et al. (2015) used TLC to study the maturity of research in Alzheimer's disease drug discovery. This study used the cumulative count of scientific publications in the domain to quantify the S-curve. The authors argue that the knowledge accumulation, indicated by the number of scientific publications in the sector, is an indicator of technology maturity. The authors positively demonstrate that successful new molecular entities in Alzheimer's disease drug discovery arise from established technologies whereas failures indicate immature technology. When using TLC to evaluate the technology of an invention, one typically estimates the developmental stage of the technology in the domain through indicators such as knowledge accumulation (Beierlein et al., 2015; McNamee & Ledley, 2013). Thus, the underlying assumption is that if the technology of the domain has reached maturity, then the technology of the invention being investigated should have reached maturity.

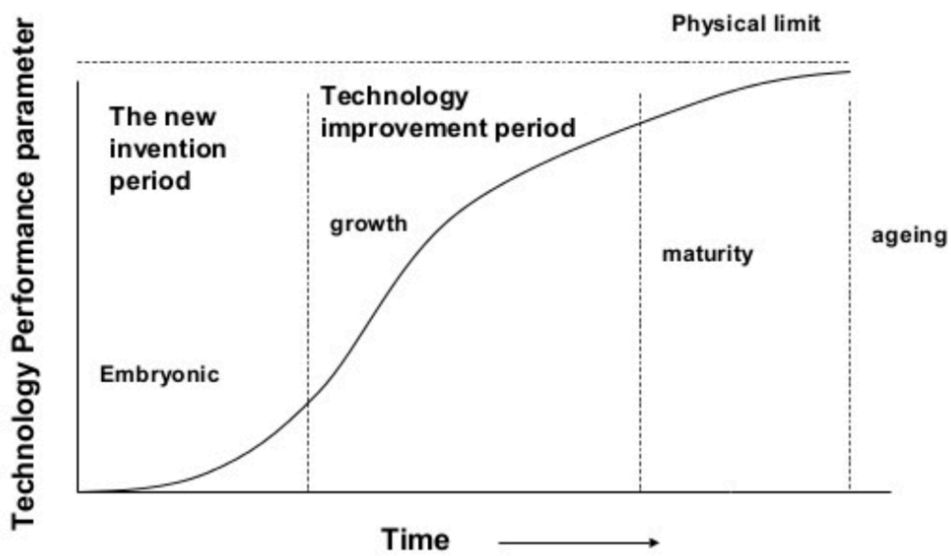



**Figure 2-2: Technology Growth Curve**

However, in studying the technology S-curves, Christensen (1992a) notes that the maturity of a technology although clearly visible through the S-curve in retrospect, is actually a dynamic phenomenon from a managerial perspective. Moreover, Christensen notes, "…nobody knows what the natural, physical performance limit is in complex engineered products." (p. 344) Thus, when it comes to upcoming technologies, it is unclear whether or not the S-curve has reached its slowing point (or even end point) except in retrospect.

### 2.2.5 Bibliometrics

Bibliometrics is the statistical analysis of publications such as journal articles and patents. Knowledge accumulation, indicated by the count of research and development publication gives an approximation of the technological developments in a sector. This understanding can then help us estimate the growth stage of the technology. Bibliometric analysis using patent data is increasingly becoming popular amongst technology forecasters. Many scholars are harnessing the information available from a patent document in an attempt to assess the technical value of the patent. Simple patent counts have been considered as indicators of the amount of research activity of an organization (Pavitt, 1985). Patents indicate the technological strength of a firm, which in turn is indicative of its growth (Belenzon & Patacconi, 2013; O'Neale & Hendy, 2012). Hence on an organizational level, patent counts are indicators of the value of a firm (Hall et al., 2005) and on a national level, they indicate the growth in the economy. The information provided in a patent document helps us understand the knowledge background and its quality, which in turn can assist in the evaluation of the technology. Moreover, this information is available freely thus, making it an ideal data for technology evaluation.

### 2.2.6 TRIZ

The theory of inventive problem solving (*Teoriya Resheniya Izobretatelskikh Zadatch* in Russian) or TRIZ is a problem solving and forecasting tool developed by Soviet scientist Genrich Altshuller. TRIZ uses the understanding of evolution of technologies and provides a structured process for projecting the future attributes of the present-day technology by assuming that the technology will change in accordance with the Laws of technological evolution (Barbulescu & Ionescu, 2010). TRIZ uses three main descriptors to assess the developmental stage of a technology on the S-curve: number of patents per time period, level of innovation per time period and technical performance per time period. Each descriptor has a characteristic profile. A composite analysis of these profiles provides clues to the technological maturity. Some studies such as those by Rahim et al. (2015), Lovel et al. (2006) and Yu et al. (2014) demonstrated the use of TRIZ in evaluating growth stage of technologies. A survey by Ilevbare et al. (2013) however, revealed that the primary challenges in the application of TRIZ is its complex and rigid methodology. One requires a deep understanding and practical experience of the process before being able to produce effective results. The time requirement to achieve such understanding makes it unreachable for many people.

In summary, qualitative methods, such as Delphi techniques and TRL, primarily rely on expert opinions. When using the TRL scale, a subject matter expert is required in order to assign the appropriate TRL level to the research project. An outsider, such as an investor, may not be able to judge the TRL level based on the technical information. The underlying assumption behind relying on expert opinions is the belief that the expert has spent enough time working in the sector to understand the current progress, existing challenges, and potential solutions to those challenges. However, literature warns us of the risks in relying only on expert opinions (Tetlock & Gardner, 2015). In addition to being expensive, opinions also run the risk of being biased. Employing expert opinions also becomes unreasonable when it comes to sorting through a cohort of inventions for the purpose of identifying the best one. Technology managers and investment bankers often come across such situations where they need to choose the most appropriate invention amongst the various available ones. Quantitative techniques such as TLC and bibliometrics are based on the knowledge generation in a sector. As the research activities progress in a sector they add to the existing knowledge about the technology. This knowledge helps inventors identify the most suitable methods for solving a specific problem posed by the sector. Information on prior knowledge within a sector is readily available in the form of scientific journals and patents. Moreover, these techniques can also be automated to a certain extent thus, enabling the analysis of multiple technologies at a faster pace. This, combined with the fact that the quantitative techniques are not subject to opinion preferences, makes them an ideal forecasting tool for investors and research managers.

## 2.3 Patent Based Technology Evaluation

Patent analysis is a branch of bibliometrics that is increasingly being adopted as a management tool. This form of analysis informs the managers about the competitive landscape of the technology, potential collaborators, infringement possibilities and future product development pathways. Over time patent analysis has grown with experts proposing a number of different patent evaluation methods. Patent based evaluation techniques rely on the relationship between the focal patent and its variables, such as citations, claims, processing time and others. These variables may be derived either through single-level relationships or multiple-level relationships. Single-level relationships only consider the factors that directly affect the patent value while the multiple-level relationships also take into account indirect effects. In this section I provide a summary of different patent analysis techniques described in the literature. I highlight the challenges in some of these techniques and argue towards a potential solution that involves the structural analysis of patent data.

### 2.3.1 Studies based on single-level relationships

In bibliometric studies patent attributes (application and publication dates, claims, technology classification, etc.) have been used in various combinations to determine the trends in the behaviour of a technology and its inventors. Each attribute of the patent document gives insight into how the technology came into being and is considered an indicator of the value of the patent. The earliest technology assessment techniques used this data to evaluate inventions. These studies are often based on single-level relationships and only consider the patent attributes that have a direct relationship with the patent. A summary of these studies is presented in TABLE 2-1.

**TABLE 2-1: Summary of studies on patent attributes**

| Patent attribute | Relation between the patent attribute and patent value | Limitations |
|---|---|---|
| Simple patent count | More patents = More research (Nikzad, 2013; Pavitt, 1985) | Does not account for the quality of research |
| Examination time (section 2.3.1.5) | Longer processing time = Higher forward citations (Lin et al., 2007)<br>Shorter processing time = Higher private value (Volodin, 2012) | Longer processing times can also be a result of administrative delays |
| Technology Classification (section 2.3.1.7) | Broad range of classifications = divergent technology(Park & Yoon, 2014) | Existence of two types of patents classifications (IPC and USPC) and lack of concordance between them poses difficulty in analysis (Adams, 2001) |
| References (section 2.3.1.8) | References to scientific literature = Basic invention (Carpenter & Narin, 1983; He & Deng, 2007) | Inconsistent results and lack of active research |
| | More references = More valuable technology (Lin et al., 2007) | |
| Claims (section 2.3.1.4) | More claims = More valuable patent (Baron & Delcamp, 2011; Lerner, 1994) | US inventors tend to have substantially more claims per patent than inventors of other countries |
| Patent Family (section 2.3.1.2) | Bigger family size = More important patent (Harhoff et al., 2003; Sternitzke, 2009) | Bigger family size is mostly seen in corporate patents. University patents, which are more basic and hence important for successive inventions often do not have a large family |
| Inventor | Group inventors = Higher citations (Breitzman & Thomas, 2015; Wuchty et al., 2007) | Varies from sector to sector. |
| Citations (section 2.3.1.1) | Highly Cited Patent = More innovative technology (Carpenter et al., 1981; Verspagen, 2007) | Citations take time to accrue and hence this measure cannot be used to evaluate new inventions |
| | Highly Cited Patent = More research funding | |
| | Highly Cited Patent = More valuable technology (Ellis et al., 1978; Narin, 1987; Trajtenberg, 1990) | |
| | Highly Cited Patent = Better corporate performance (Hall et al., 2005; Jaafari, 2012) | |
| | Self-citation = Higher market value (Hall et al., 2005) | |
| | Citations across geographies or classifications | |

| Patent attribute | Relation between the patent attribute and patent value | Limitations |
|---|---|---|
| | = Knowledge diffusion and spill over(Hu & Jaffe, 2003) | |
| Renewal (section 2.3.1.3) | Patent renewed = Higher value (Bessen, 2008a) | Patent protection being renewed indicates the commercial value of the patent and doesn't necessarily indicate the technical value. |

#### *2.3.1.1 Forward citations*

One of the highly studied aspects of a patent is the number of citations it generates. There are an ever-expanding number of studies in this area. A patent being cited is an indicator that it has some important piece of knowledge, which is vital for the successive technologies. Taking inspiration from bibliometric studies of journal articles, Carpenter et al. (1981) first studied the relationship between patent citations and patent value. They analysed the citations of 200 patents and concluded that the citations received by patents representing innovative products were higher than that received by the control samples. Nine years later a study by Trajtenberg (1990) on patents relevant to computed tomography scanners showed that patent citations have a strong relationship with economic value of patents. This study paved the foundation for the bibliometric approach to patent analysis. Later studies associated citations with technical value (Albert et al., 1991), market value (Hall et al., 2005) and private value (patents considered as high value by the company) of a company (Fischer & Leidinger, 2014; Harhoff et al., 2004). Though citations have been accepted as a patent value indicator, it is also understood that since citations take time to accrue and therefore, cannot be used to evaluate recent patents (Hall et al., 2005). By the time a patent has accrued enough citations, its success or failure is already apparent through its performance. On the other hand, at times the technical value of a patent goes unrecognized for a long period and is cited only at the later stage of its life (Cano & Lind, 1991; Ohba & Nakao, 2012). Fallah et al. (2009) attempted to predict the lifetime citation count of patents based on the citation data in their early years. This model was however ineffective for new patents (less than five years old). Therefore, forecasting techniques based on forward citations are not actually predictive.

#### *2.3.1.2 Patent Family*

Since the concept of "worldwide protection" doesn't exist, an inventor has to apply for protection for the invention in each country in which a market potential exists. Because most countries charge an annual fee for the maintenance of the legal protection in addition to the application fee, gaining patent protection in multiple countries becomes an expensive process. In such a scenario, an inventor would proceed to protect the invention in multiple countries only if a market potential exits, which therefore indicates the value of the invention. Hence, a larger patent family size (invention protected in a number of geographic regions) is an indicator of the inventors' perceived value of the invention (Fischer &

Leidinger, 2014; Harhoff et al., 2003; Sternitzke, 2009). Nakamura et al. (2015) claim that the technology trends can be explained better when the complete patent family is taken into consideration for the analysis. However the inherent difficulty in using patent family information for evaluating patents, as Simmons (2009) explains, is that patent families are not defined by national or international laws. They are created by databases, thus resulting in different definitions. If a researcher is unaware of these definitions, it may lead to data errors. Guellec and de la Potterie (2000) note that patent value increases with family size until a threshold limit, beyond which it decreases. The authors suggest that an excessively large family size may indicate immaturity of the inventor, since for most technologies, protection in the largest markets should yield sufficient returns on value.

#### *2.3.1.3 Renewal Data*

Most countries charge an annual fee in order to maintain the legal protection granted to the patent. The obligation to pay renewal fees to keep patents alive implies that there is an existing market or that the patent holder sees a potential market for the invention, hence making it valuable. Using this understanding, Pakes (1984) developed a model that used patent renewal data to estimate the value of the patent. This relationship was later confirmed by other studies (Bessen, 2008b; Zhang & Chen, 2012).

#### *2.3.1.4 Claims*

The claims of a patent define the limit of exactly what the invention does. Based on these, the patentee has a right to exclude others from utilising the methods described in the claims. Hence, the infringement litigations revolve around what has and has not been defined in the claims. A patent that is broad in scope (more claims) is exposed to potential infringement and therefore, could lead to litigation. A likelihood of litigation is an indication of the value of the invention. Lanjouw and Schankerman (1997) found that the number of claims is associated with a greater probability and frequency of litigation. While Lanjouw and Schankerman (1997) described the scope of a patent through the number of claims, Lerner (1994) measures this value through the number of International Patent Classifications assigned to the patent. Gambardella et al. (2008) found a positive relation between claims and patent value in this study of European patents. Other studies too found similar results (Baron & Delcamp, 2011; Lin et al., 2007). Tong and Frame (1994) observe that in measuring the technological growth of a country, patent claims are better indicators than simple patent counts. The authors also note that US inventors tend to have substantially more claims per patent than inventors of other countries. Hence, this indicator should preferably be used to compare patents within the same country. When comparing across countries appropriate techniques should be employed to first normalize the number of claims.

#### *2.3.1.5 Examination time*

The time duration between the application of a patent and its grant is known as the examination time. Lin et al. (2007) note that biotechnology patents receiving a higher number of citations have a longer examination time. The authors argue that an examiner may need longer time to judge whether an important patent should be granted or not. In contrast research by Volodin (2012) shows that high value patents have a shorter examination time. The author argues that a shorter examination time means that the inventor (or assignee) is able to enjoy the monopoly provided due to the grant of the patent for a longer time. This monopoly translates to profit from sales of the product (based on the invention) or licensing of the invention, which ultimately reflects the value of the invention. The author further argues that the discrepancy in the conclusions drawn by different studies in this aspect may be due to the difference in the methodology adopted in calculating the examination time.

#### *2.3.1.6 Self-Citations*

Another type of citation that has received attention is self-citations. Jaffe et al. (1993) describes self-citations as a citing patent that is assigned to the same party as the originating patent. These indicate that the firm has a strong competitive position in that specific technology. Hall et al. (2005) in their study of patents of firms listed in Compustat database found that self-citations are more valuable than external citations. In other words, the market value of the firm increases more on receiving a citation from the firm itself than from outside. Alcácer and Gittelman (2006) observe that examiners are more likely to add self-citations of individuals raising questions on whether self-citations can truly be considered as evidence of knowledge flow. The authors postulate that inventors may exclude self-citations due to strategic reasons, leaving it to examiners to find those citations.

#### *2.3.1.7 Technology Classification*

Taking a different approach, He and Luo (2017) explored the effect of conventionality and novelty on the value of inventions. Novelty indicates that an invention is unexpected and surprising. They argue that if the IPC codes of a patent had seldom been assigned to other patents in the sector, this invention's combination of prior knowledge domain can then be termed novel. Using citations as proxy for value, the authors observed that inventions with medium level of conventionality with any level of novelty lead to high value inventions. Inventions with high-level conventionality do not result in high value. Since this method uses data on references and IPC codes only, it may be useful in the evaluation of new patents.

#### *2.3.1.8 References*

Reitzig (2004a) states that to be deemed useful, an indicator should be a valid correlate of patent value and should be available early in a patents life to allow for evaluations. According to this study, of all the patent attributes that are indicators of patent value, studies based on forward citations have the strongest empirical evidence. However, this measure is not available in the early part of the patent life rendering it impractical for evaluating young patents. Moreover, for most of these patent indicators the information becomes available about 18 months after the filing date of the patent (Reitzig, 2004a). This time frame may vary based on the patent office. Thus, one would need to wait for at least this period of time in order to be able to assess the patent based on these indicators. It should also be noted that most of the single-level based indicators, such as citations, patent family, patent renewal and litigation data, express the value of the invention based on external views. In other words, they value an invention as important if others say it is important. The upside of this approach is that such external views indicate validation of the technical value. The downside however is that it takes time for others to try and validate a technology.

The use of references however may be seen as an exception to this disadvantage. References (also known as backward citations) indicate the state of art of the field of invention. They describe the knowledge on which the invention is based. The importance of this knowledge base could be indicative of the value of the invention itself. The advantages of using references in patent evaluation are two-fold;

a. Unlike forward citations, references are static measures. Since they do not change with time, the value indicated by them would not be time-dependent.
b. Since the inventors have a good understanding of the prior art, this measure can be used to evaluate the invention even before the patent has been granted provided the inventor provides a comprehensive list of the prior art.

References have been used to trace the ancestors and knowledge base of technologies (Calero-Medina & Noyons, 2008; Cooray, 1985; Hummon & Dereian, 1989; Lin et al., 2011). Literature has perceived the role of references in the evaluation of patent value in different ways. For example, References to non-patent literature have been shown to be a linkage to science and indicate the scientific value (valuable in solving general laws rather than a specific technical problem) of the invention (Carpenter & Narin, 1983; Trajtenberg, 1997; Verbeek et al., 2002). A higher number of references indicate a larger knowledge input, which may lead to innovative products (Hu et al., 2012). A broader spread of technology classes of the references indicates the "originality" of the patent (Trajtenberg, 1997). It is observed that radical patents refer to emergent knowledge that belongs to different technical domains (Schoenmakers & Duysters, 2010). Other scholars have argued that radical patents are pioneering creations and hence do not cite preceding technology (Banerjee & Cole, 2010).

While the use of references comes with its own limitations[4], it has been shown that technology domains with higher backward citations show a higher growth (Chen et al., 2010). In some studies of a single

4. Researchers have raised concerns that references may not be true indicators of knowledge flow since they are added both by the inventor and the examiner (Alcácer & Gittelman, 2006; Jaffe, 2000). Criscuolo and Verspagen (2008) in a study of European patents conclude that only inventor citations should be considered as knowledge flow indicators. However, Alcácer and Gittelman (2006) argue that inclusion of citations is often a strategic decision by the inventors which is based on potential infringement and holdup threats. Hence the bias introduced by examiner citations many not necessarily be negative.

technology sector or geography, a positive relationship was observed between backward citations and patent value (Harhoff et al., 2003; Lin et al., 2007). However, such a relationship was not identified by other studies (Lanjouw & Schankerman, 1997; Nair & Mathew, 2012; von Wartburg et al., 2005). The reason for the discrepancy in the results may be because only single-level data was considered in these studies.

### 2.3.2 Studies based on indirect relationships

Scholars argue that single-level relationships do not take into account the technological complexity and the knowledge background of the invention (Atallah & Rodríguez, 2013; Hu et al., 2012; Yang et al., 2015). In order to account for these, one needs to consider the relationship with other knowledge entities that have an indirect effect on the invention. Such thinking has given rise to the structural view of inventions.

When a patent is cited by successive patents, a link is formed between them. This link represents the knowledge shared between the inventions. One can trace these links both backward and forward in time through a patent's references and citations, respectively. This entire assembly comprising of the patent with its references and citations forms the citation network of the patent and provides a structural view of invention. The earliest citation networks were drawn with an intention to view the science and technology maps. For example, Small et al. (Small, 1997; Small & Griffith, 1974) sketched the paradigm map of physical science using co-citation links and journal articles. Börner et al. (2003) used both backward and forward citations to develop mapping techniques for visualizing the structure and dynamics of science and technology. Chen and Kuljis (2002) on the other hand mostly worked with forward citations to visualize knowledge domains and further analyse them. Chen worked with both patents and scientific publications to develop explanatory visualization techniques.

Taking into account the knowledge background and the technological complexity, scholars started asking questions such as: how does the importance (value) of the knowledge base affect the value of the invention? Or how does the applicability (across various sectors) of the invention affect its value. To answer some of these questions Trajtenberg (1997) used the concept of basicness to describe the value of an invention. Basicness explains the fundamental features of an invention such as its originality and closeness to science. The author also introduced the measures IMPORTB and IMPORTF. The author argues that important inventions provide a base for numerous subsequent technical changes. Thus, the measure IMPORTF is intended to capture the technological impact of an invention. This indicator basically measures the descendants of an invention and their importance. IMPORTB, the backward-looking measure, on the other hand reflects the importance of an invention based on the importance of the knowledge it is grounded on. Though these measures use references in their construction, the importance of these references is measured through external views, that is to say its forward citations.

To study the effect of indirect citations Rousseau (1987) first proposed a mathematical technique. Using two generations of references Rousseau demonstrated a technique that could be used to find out which publications have had the greatest influence on the development of a research. The author however notes that using more than four generations of references may be unreasonable, considering the large matrices one has to handle. Hu et al. (2011) further expanded this concept and included both the forward and backward citations in their proposed indicators. This article however focused on identifying and defining different generations of citations. Both these studies used journal articles as their data.

This idea was later extended to patents by the same set of authors (Hu et al., 2012). The authors proposed a set of technical value measures based on the structural indicators of an ego patent citation network (i.e. citation network of a specific target patent). The purpose of the study was to include the influence of technological complexity on the value of invention. Using an independent sample t-test the authors showed that these measures could distinguish between a high value and low value sample sets. However, Hu et al. (2012) used the commercial success (return on asset of the company using the patent) as a proxy for the value of patent. Return on asset is a measure of the profit a company earns in relation to its overall resources. Though this measure informs us of the performance of the company on the whole, it does not divulge much information on which one of the assets is the most contributing one towards the profit. In case the company owns multiple intellectual properties, extracting the value of a specific invention from that cohort would be a challenge. In this work, the authors incorporate only up to two generations of citations in their measures. It may be argued that mere two generations may not represent the complete knowledge flow in the invention. Also, most of the measures include forward citation counts, which may limit the applicability of these measures to older patents.

Wartburg et al. (2005) provided further proof that multiple-level relationships are superior when it comes to revealing technological developments in a sector. The authors used 2 generations of patent citations for revealing scientific paths of technological development. The study shows that single-stage citation analyses are insufficient for revealing specific paths of technological development. This study used a combination of network analysis along with bibliometrics to gauge technical value of inventions.

Another question raised in the use of single-level relationships was the possibility of missing knowledge links. For various reasons, it is possible that some of the vital knowledge link to the technology may be ignored. In such a case, single-level indicators would convey an incomplete picture of the technology. A solution was provided for this in a research by Yang et al. (2015). In this study, the authors combine 4 different types of citations (direct citation, indirect citation, coupling and co-citation network) to create a comprehensive patent citation network. The results indicate that such a network can be used to predict the technical value of patents. The authors note that such a comprehensive patent citation network fills the gap left by missing citation links that are otherwise not captured by single level citation networks. The complex task of constructing multiple networks and their integration may hinder in the use of this procedure in technology managerial applications.

The results from these studies are encouraging, especially because they show that multiple level indicators are more effective than single level indicators. However, the question remains: how deep does one need to dig in order to get a complete picture of the knowledge structure of the invention? Unfortunately, the answer to this question is not straightforward because not all the knowledge that has contributed towards the invention is documented. Some of the knowledge remains in tacit form. Moreover, the explicit part of the knowledge may be documented in different forms, such as research articles, patents, conference proceedings, etc. In an ideal situation, one should consider all forms of this knowledge to build the knowledge structure of the invention. This however, is hardly practical. Thus, when considering only one form of the data such as patents, considering all the known generations of the citation network may reveal a comprehensive knowledge structure. Three notable studies by Ellis et al. (1978), Bosworth (2004) and Atallah and Rodríguez (2013) included the effect of all the generations of the citation network of an invention in their study.

Probably one of the first studies that used multiple-generation citations was carried out by Ellis et al. (1978). This research was conducted to study the key milestones in the technological development of a sector. Starting from 10 patents from five different sectors, the authors traced the citations all the way back to the earliest patents found in the sector. The authors conclude that such studies could be valuable for forecasters in identifying topics of high current interest. This was an exploratory study aimed at assessing the usefulness of patent citation networks and did not aim to assess patent value. Bosworth (2004) demonstrated the use of multiple round citations to explore the ancestral trees of patent. In this study Bosworth observed the indirect citations made to two US patents between the periods 1976-2000. The aim of this study was to observe the interaction between science and technology bases and to study the impact of science and technology spillover. Bosworth's study was successful in demonstrating that tracing the technological origins of a patent through multiple round citations reveals higher level of details such as spillover activity and changes in technology fields. This study however had certain limitations. Firstly, the study demonstrated the method on only two patents thus, raising questions on the robustness of its results and applicability across sectors. Secondly, Bosworth's data was truncated to mid 1970's due to the choice of database (USPTO). Hence the ancestral tree presented in this study may still be seen as an incomplete picture. Finally, Bosworth did not attempt to explain patent value through this knowledge structure. The latter point may be seen more as a limitation in scope of the study rather than limitation of the methodology.

Following Bosworth's work, Atallah and Rodríguez (2013) proposed a new measure of patent quality that takes into account the quality of all the patents involved in the chain of citations starting from the target patent. Unlike Bosworth's work, this study incorporates forward citations. In their statement, "…there is no reason to believe that backward citations contribute in any way to the quality or the importance of a patent", the authors reveal the reason for choosing forward citations for the analysis. The results from many studies (Harhoff et al., 2003; Lin et al., 2007; Reitzig, 2004b) however, contradict this claim made by Atallah and Rodríguez (2013). The authors in this study demonstrated that the new metric could be used as a measure of patent quality and more importantly in comparison of patents of similar ages. The fact remains that since this method is based on forward citations, it cannot be used on recently granted patents.

The methodology adopted by my dissertation may be seen closest to the works by Ellis et al. (1978), Bosworth (2004) and Atallah and Rodríguez (2013).

### 2.3.3 Complex Networks theory perspective of patent value

The knowledge structure of patents has also been explored through complex network analysis. Newman (2001) paved the path in the field through his work on scientific collaboration networks. Though his research used scientific journal articles and their citation, work on patent networks soon followed. Complex network analysis investigates structures through the use of network and graph theory. It measures the relationship and flow between various nodes in the network. This field of science is increasingly being applied to patent citation networks to understand knowledge flow (Balland & Rigby, 2017; Bell & Zaheer, 2007; Geng & Wang, 2012; Nemet & Johnson, 2012; Schilling & Phelps, 2007; Thomas & Zaytseva, 2016) technological growth patterns (Guan & Shi, 2012; Hung & Wang, 2010; Ye, Yu, & Li, 2013) and technical value (Al-Laham & Amburgey, 2010; Cho & Shih, 2011; Goetze, 2010; J. C. Wang, Chiang, & Lin, 2010) amongst other things. In a patent network the nodes could be patents (Marra et al., 2015), organizations (Sun, 2016), inventors (Chen & Fang, 2014), collaborations (Guan et al., 2015) or patent classifications. The ties between these nodes are often the citation links that facilitate knowledge flow. Studies utilising network analysis to explore patent networks typically measure topographical features of the network such as centrality, average degree, clustering coefficient, path-lengths, network-density and network-size. From a patent citation networks perspective, a patent with high clustering coefficient describes the connected level of the research subject in the published articles. The closeness centrality of a patent indicates its efficiency in spreading information whereas the betweenness centrality measures the ability of a patent in acting as a broker of information. The objective in these studies was to understand the knowledge transfer process between entities (Al-Laham & Amburgey, 2010; Choe et al., 2013; Guan et al., 2015; Li et al., 2007). Van Der Valk and Gijsbers (2010) give a detailed description of how social network analysis (SNA) is used in innovation studies.

Chang et al. (2016) applied the structural indicators described in complex network analysis along with patent attributes to distinguish between litigated and non-litigated patents in LED technology. The authors argue that the patent value reflects the flow of technological knowledge. This technological knowledge is ever evolving due to the citation relationships that keep growing. Hence, patent value is dynamic, and can be studied through graph theory. The authors note that a patent's in-degree and out-degree centrality have a positive relationship with patent value. They also note that the effect size of a node negatively affects patent value. In-degree of the node is the patents it refers to while the out-degree is the citations it receives. Effect size reflects the non-redundant information in the relationship of patent and adjacent nodes. In addition to showing the potential of complex network analysis as a patent evaluation technique this study reiterates the fact that forward citations are indicators of patent value. Similarly Wang et al. (2012) studied biotech patents in Taiwan and Korea granted in US. This study used patent renewal decision as proxy for patent value. However, it is unclear how the patent citation networks were constructed in these studies.

Suh (2015) explored the effects of structural patent indicators such as centrality (degree, closeness and betweenness) on patent price in smartphone and drug & biotechnology industries in USA. Suh used forward citations to build the citation network. The author concluded that structural patent indicators are superior to mere forward citation counting as indicators of patent price. Suh also noted that the effect of these structural indicators is different for different industries and therefore, should be chosen accordingly. However, the patent networks mentioned in these studies are based on forward citations, which is a dynamic quality. The number of forward citations received by an invention increases with time and moreover citations take time to accrue. Thus, value indicators based on forward citations are unavailable when the patent in question is new.

In order to be able to determine the patent value in the early years of patent life, Wang et al. (2010) utilised the measures of brokerage and closure of patent citation network. The authors used forward citations and patent renewal data as proxy for patent value. The patent citation network was constructed using two forward generations and two backward generations of the focal patent. The study showed that for technologies in mature developmental stage, brokerage position influences the changes in forward citations while high closure position is more likely to have fewer renewal decisions. The authors argue that the assignees of the patent can use these patent indicators to determine the position of their patent in the network to make decisions regarding future development of the patent. It may be argued that depending on the sector, a considerable amount of time may be required for one to observe two generations of forward citations of a focal patent. Thus, the applicability of this method on new patents needs further validity.

Weng and Daim (2012) examined how being in a core or peripheral position within a network contributes to technological developments. The authors observed that technologies occupying the core position in a network are in propensity for exploitation in succeeding or derivative technologies. While technologies located in periphery position of network are likely to lead to seminal technologies.

Patent value has also been studied from the perspective of the knowledge creators, i.e., the inventors and/or the organizations. Jiang and Zhou (2014) studied university – industry collaboration networks to understand the effect of the knowledge structure on knowledge production and patent value. The authors concluded that the effect of small-world phenomena on the patent value is parabolic (i.e. it increases up to a specifically established scope and then decreases). A network is said to display small world phenomenon if most of its nodes are not neighbours of one another but can be reached through a series of small number of steps. A small world network tends to contain cliques or sub-networks, which are highly connected nodes. Also, most pairs of nodes are connected by one path. Patent citation networks have been found to display small world phenomena (Hung & Wang, 2010; Ye et al., 2013). Based on the findings Jiang and Zhou (2014) suggest that the managers should pay attention to the social networks when selecting location for their firms, as scattering would lead to delayed communication while clustering would lead to redundancy of information.

To understand the importance of an inventor in the value of patents, Beaudry and Schiffauerova (2011) studied Canadian inventor collaboration network in the field of nanotechnology. They concluded that more central inventors contribute to increasing patent quality. The authors argue that different network structures and characteristics have different impacts on knowledge sharing between individuals and their organizations thereby influencing innovation creation. This research shows the importance of exchange and circulation of knowledge within groups of socially connected agents. This results in fast knowledge accumulation and high invention rates. The authors used the measure of number of claims, as a proxy for patent value. Eslami et al. (2013) found small-world properties in collaboration network of Canadian biotechnology inventors and scientists. Their research found a strong association between the way scientists are connected among themselves in collaboration and the quality of the research that comes forth such collaboration. Studies that evaluate a patent based on the collaboration network, work on the assumption that the past performance is a reflection of the quality of the future work. This may be an over-optimistic assumption.

#### *2.3.3.1 Knowledge structure robustness and patent value*

Network robustness, described in statistical mechanics of complex networks, tests the ability of the network to continue functioning despite disruptions. Disruptions in a network occur when its nodes and/or edges are removed progressively such that the network disintegrates, that is, nodes become disconnected from the network. While there is a vast body of literature that explores the robustness of different network structures, studies on robustness of knowledge structures is still very limited. Literature defines knowledge networks as structures where knowledge entities are connected together due to the knowledge they share (Phelps et al., 2012). The entities, which form the nodes, are often individuals, groups, organizations, or knowledge repositories. The studies from the former group (where the entities are individuals, groups or organizations) often associate robustness of the network with knowledge erosion (Wang & Shen, 2014; Xi & Dang, 2007) or knowledge diffusion (Zhang et al., 2016). Knowledge erosion occurs when employees leave an organization, taking away with them the knowledge attached to them. These studies address the question of communication strength between entities (Maggioni & Uberti, 2009; Protogerou et al., 2007), propose better ways to measure it (Xi & Dang, 2007) and accordingly suggest methods to improve network configuration (Dodds et al., 2003; Wang & Shen, 2014).

However, individual, group and organizational networks cannot be considered as knowledge structure of individual inventions because they depict the knowledge possessed by the inventor or organization on the whole. For example, organizational knowledge is a summation of knowledge held by all the individuals in the organization of which the knowledge network of an invention is a subset. Hence, the effects of knowledge unit interactions in a network felt by a single invention may not be similar to the effects observed on an organizational level. Thus, one cannot apply the results observed in these studies to individual inventions.

Studies on robustness of knowledge repositories are rather scarce. I came across only two such studies. Massimo (2012) studied a large-scale journal citation network comprising of over 6000 nodes with an intention to understand information diffusion. In this exploratory work, the author tested the robustness of this network using four node-attack strategies; degree, eigenvector, closeness centrality and betweenness centrality driven. The author concluded that betweenness centrality driven attack is the most damaging strategy for a journal citation network. Zhou et al. (2016) used journal citation network to analyse the performance of scientific journal ranking system. The authors describe robustness as the strength of the journal ranking system in resisting manipulations or malicious attempts of some authors in pushing up the influence of their publications.

Both these studies used journal citation networks for their analysis. Certain differences exist between the citation practises in journals and patents. Citations in journal articles could result from a number of reasons such as referencing influential work, biased or self-interested reasons, affirming or dissenting prior work etc. On the other hand references of a patent are considered more pertinent to the subject matter. Meyer (2000) concludes that differences between academic and patent citations, makes it difficult to simply transfer the theoretical framework from one field to the other. Patent citation networks represent the knowledge network of inventions. These structures reveal to us how knowledge flows from different knowledge entities to form an invention. To the best of my knowledge researchers are yet to address robustness of patent citation networks and its significance to the technical value of an invention.

#### *2.3.3.2 Main Path Analysis*

Main path analysis is a technique based on complex network analysis that helps identify the major paths in a citation network. This technique has been used by many scholars to determine the developmental trajectories of technological domain. Such studies can be found in the fileds of environmental science (Barbieri et al., 2016), high technologies (Bekkers & Martinelli, 2012; Huang et al., 2017), information technology (Xiao et al., 2014), medical sciences (Leydesdorff et al., 2016) and many other fields. This technique is helpful in revealing the knowledge roots of domains and the various progress paths.

Complex network analysis-based patent evaluation techniques, where nodes represent the patents, suffer the same disadvantages as single-level relationship-based techniques; they cannot be applied on new patents. A recently granted patent appears on the patent network as a node with 0 (zero) out degree. In other words, while it will have references, it will not have citations. As a result, some of the network metrics, such as node degree, clustering coefficient and centralities will not reflect the true value of the patent. The review of technology evaluation literature points to two specific gaps:

1. Current studies only consider a partial citation network while evaluating the technical value of inventions.
2. The current technical value measures are not predictive as they incorporate the count of forward citations. Thus, they cannot be applied on new inventions.

## 2.4 Summary

The literature review reveals that there is a strong dependence on the opinion of domain experts to assess the value of an invention. However, it is often difficult to find such experts. Moreover, the expert opinion is known to be subject to bias. One of the potential solutions in overcoming this limitation is to examine the prior knowledge leading up to the invention as an indicator of its technical value. The knowledge accumulated in a sector is representative of the various efforts that have taken place in the sector over time in solving various technological problems. This knowledge gathers and grows over time and forms its unique structure. Analysis of the structure of knowledge accumulation should give us indications on the maturity of the technology and therefore its technical value. A potential solution to assessing the knowledge structure of an invention is through patent data. When applying for a patent, it is a legal requirement (depending on the jurisdiction) for the inventor to disclose all the prior art in relation to the invention. This prior art, which is present in the form of references, gives a window to the knowledge accumulation and thus, the knowledge structure of the invention.

While much appreciable work has been done in patent analysis in relation to technology evaluation, none of the methods yet are truly predictive. Forward citations and patent family members take time to accrue. Hence techniques based on these parameters fail to identify valuable inventions when the patent in question is new. Methods based on processing time can only be used on granted patents.

Much investment has already been done on inventions by the time they have been granted intellectual property rights. Thus, from a technology managerial perspective foresight at this point may not be much beneficial. While methods based on backward citations can be utilised on newly granted patents, the results from various studies do not seem to agree with each other. These surface-level indicators provide only a partial picture of the patent value. The application of complex network analysis in this area has also been growing steadily. However, this field is still unable to demonstrate a process to predict the technical value of new inventions.

Studies that consider the knowledge structure of the invention take into account the effect of technological complexity and knowledge flow on the value of the invention, and hence might provide a clearer picture. While this line of thinking seems promising, it still requires some work to bolster its foundations. For example, the fundamental question that may arise is, how can one observe the knowledge structure of an invention? Out of the many different possible ways that can be used to represent the knowledge structure, what kind of a structure would then let us predict the technical value? These questions would then lead us to explore the characteristics of the knowledge structure that could be the indicators of the technical value.

# 3 KNOWLEDGE STRUCTURE

## 3.1 Introduction

The structure of a system shows the arrangement of its different elements and how they interact with each other. This structure gives us an insight into how the system operates. For example, a DNA (Deoxyribonucleic acid) molecule, which carries the genetic instructions of any living organism, is composed of repeating units of nucleotides. This structure of a DNA is essential to its functioning. The structure of an atom is composed of a nucleus, electron cloud and sub-atomic particles. This configuration of electrons, protons and neutrons in an atom determines which atoms it can interact with and ultimately its properties. Understanding the underlying structure of a system is the key to understanding the functioning of the system. Scholars, from time to time, attempt to give a structure to the growing scientific knowledge. Such structure helps us see with some clarity the various hierarchies, different knowledge streams and changing paradigms in the scientific community.

Technologies and inventions too have an underlying structure; this is evident from the review of the technology valuation literature presented in CHAPTER 2. This structure is composed of various knowledge units that come together in the creation of the technology. This knowledge structure may hold answers to how the technology behaves. The behaviour of a technology is observed in terms of its pace and direction of growth. The knowledge structure of an invention thus, may also indicate its maturity and therefore its value.

In this chapter I draw upon the knowledge contributed by many scholars to develop my theory on knowledge structure of inventions and how it may be an indicator of technical value.

## 3.2 Knowledge creation and the emergence of a knowledge structure

For an invention, the maturity of its technology relates to the state in which all the inherent technical problems posed by the domain have been solved and the technology can be implemented into a product. Being implemented into a product or successive technologies indicates the technical value of the invention. To draw the link between knowledge structure and technical value, I investigate the journey of knowledge from its creation to becoming embedded in a product. Figure 3-1 depicts a snapshot of this journey.

Creation of knowledge begins in the minds of individuals as new ideas. Nonaka (1994) describes the process of knowledge creation as comprising of four stages – socialization, externalization, combination and internalization. Socialization corresponds to the tacit knowledge flowing from individual to the group level. Externalization leads to articulation of tacit knowledge and its subsequent formalization to make it concrete and explicit. Combination denotes coordination between different groups in the organization along with existing knowledge to combine new concepts with other existing explicit knowledge. Internalization denotes applying the combined knowledge and turning it in tacit form. It is important to note that underlying the stages described by Nonaka are the social interactions between people either individually or in groups. Such interactions enable the exchange of ideas that lay the foundation to the knowledge structure.

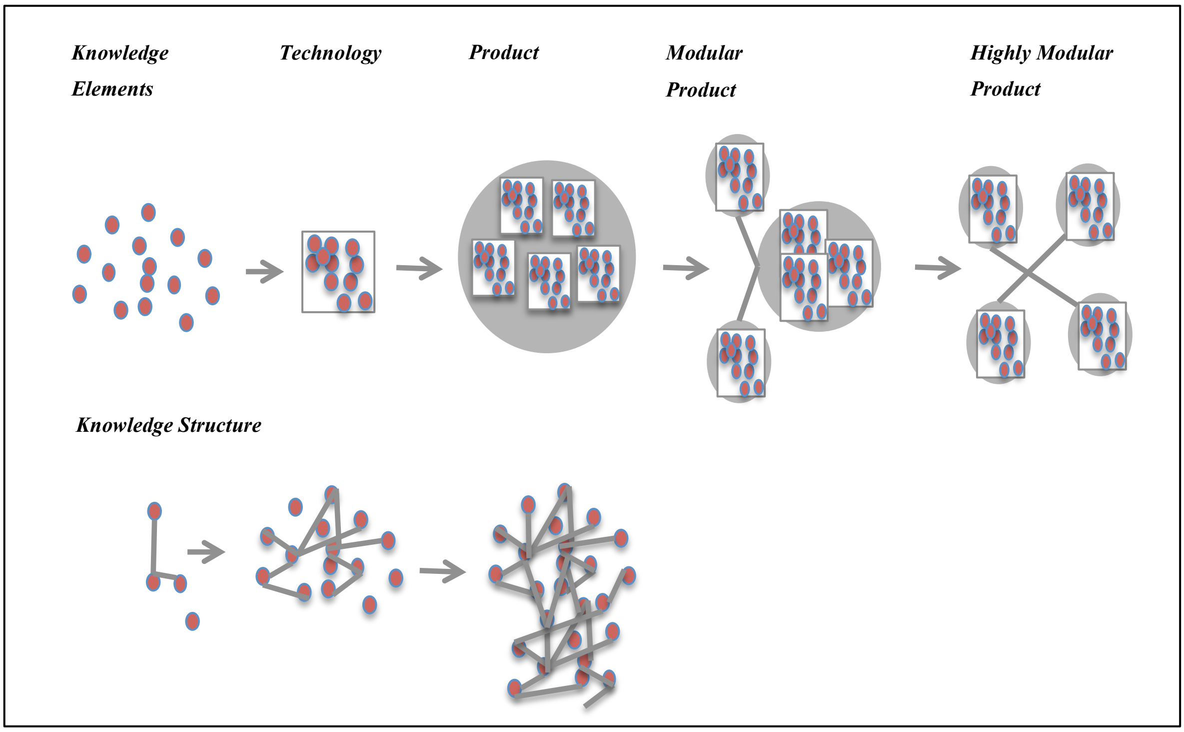



**Figure 3-1: Journey of knowledge from creation to becoming a product**

There are two schools of thoughts that try to explain the creation of knowledge that lead to inventions. The recombinant search theory argues that an innovation is an outcome of recombination of existing concepts and ideas (Fleming, 2001; Nelson & Winter, 1982). New technologies are constructed over existing technologies and eventually become building blocks for future technologies (Fleming & Sorenson, 2004; Henderson & Clark, 1990). The second school of thought argues that innovation is a gradual process resulting from slow accumulation of improvements and features. Inventors look for solutions within close proximity of the technological area and improve the technical features one at a time (Cyert & March, 1963). While there is much discussion on how new knowledge is created, there is a general consensus that the past knowledge is an important ingredient in the creation of new knowledge. Inventors turn to the existing wealth of knowledge and experiences in the sector in order to determine feasible techniques for converting the new idea into a successful invention. The exchange of knowledge to achieve this takes place through journal articles, research conferences and other such platforms. The knowledge structure of the invention begins to take shape as more of these techniques are borrowed. This knowledge structure grows further until the technology of the invention is perfected. Many studies have hinted at the existence of a structure behind every invention (Hu et al., 2012; von Wartburg et al., 2005).

The prior knowledge, which may be seen as the knowledge accumulated in the sector, is known to be a vital ingredient in the creation of the invention and subsequently the product that results from it. Researchers (Beierlein et al., 2015; McNamee & Ledley, 2013; McNamee & Ledley, 2012) have shown that unless the technology reaches maturity, it cannot be successfully implemented into products. These researchers argue that the technological maturity is indicated by the knowledge accumulated in the sector. While these studies do not draw any connection between technological maturity and knowledge structure of the invention, they reiterate the importance of prior knowledge in the success of a product (success being measured in terms of the feasibility of implementing the technology into a product).

Once the technology has been perfected, it is then implemented into a product. At this stage the architecture of the product is refined so as to improve its performance. The evolution of product performance and architecture is hypothesized to follow an S-curve (Yassine & Naoum-Sawaya, 2017). A product starts its journey with an integral architecture. With technological advances, the architecture of the system evolves in the direction of modularity. Modularity simplifies the problem of making improvements to the components within the product. This process continues until a highly modular architecture emerges (Abernathy & Utterback, 1978; Baldwin & Clark, 2000). Modularity of a product has been associated with technological progress. Dong and Sarkar (2015) argue that the fundamental limiting factor in the progress potential of a product is not the complexity of the product architecture, but rather the underlying knowledge structure of the product. Using complex networks to represent the knowledge structure of a product, they show that products with a higher potential for progress have structural characteristics that differ from products with low potential for progress. Research has also shown that the knowledge structure of an innovation influences the ease with which its existing design can be changed in order to employ new solution principles (Dong, 2017).

The results from all these studies hint not only of the existence of the knowledge structure, but also of its importance in the process of an invention becoming a product. Thus, the knowledge structure of the invention many be a suitable indicator of its technical value. The fact that the knowledge structure does not change with time makes it an ideal indicator for the assessment of new inventions.

## 3.3 Knowledge Structure of Inventions

In order to use the knowledge structure to assess technical value, the first step would be to uncover the knowledge structure of the invention. Unfortunately, when one looks at inventions in isolation, as an individual event, there doesn’t seem to exist a comprehensible pattern or structure to it. Hence while some inventions seem to need long periods of research others seem to pop up effortlessly. Some inventions are a result of group effort while a few are creations of lone inventors. For example, Breitzman and Thomas (2015) study noted that in 1997, 41% of the patents granted in US were invented by a single inventor while the remaining inventions had a team size ranging from two to more than eight. Such extreme behaviour may have led researchers such as Gupta (2012) to believe that inventions are unpredictable by nature. Gupta (2012) argues that innovations are unpredictable by nature. Efforts put towards predicting their value during early stages of the innovation often do not improve predictability. Thus, efforts should be focused on evaluating innovations that are at a later stage in the innovation cycle.

To uncover the knowledge structure of an invention, I use the description of technologies and inventions proposed by Arthur (2007). Arthur further developed the concept of recombinant search and proposed his theory on the structure of inventions. According to Arthur a technology is a means to fulfil a need by exploiting a base phenomenon. For example, a turbine exploits the phenomenon of electromagnetic induction (the relative movement between a conductor and magnetic field produces electricity) to fulfil the need for generating electricity. Most often it takes multiple technologies to fulfil a need. For example, the generation of electricity using hydropower requires the technology of building water reservoir, intake gates to control the water in the reservoir, penstock to lead the water to the power generation unit, turbine, and the generator to convert hydro energy to electrical energy and finally electricity transformer to transfer the electrical energy. Thus, a technology may be seen as a base method that exploits a base phenomenon and is supported by complementary technologies in order to do so.

Arthur defines invention as a method that exploits the base phenomenon in a way that hasn't been demonstrated before, in order to fulfil a need. The architecture of inventions too has a base method, which is supported by complementary technologies. If successfully adopted, today's invention would become tomorrow's technology. For example, the Czochralski process invented in 1915 for growing moncrystalline silicon is now a well-adopted technology for manufacturing silicon ingots. Innovation, on the other hand, is an improvement or refinement of the idea proposed in the invention (Despa, 2014). For example, James Watt and Thomas Newcomen's design of steam engine could be considered as a refinement of Papin's design (Kerker, 1961) and hence are innovations. The hybrid wind-hydro turbines may be considered as the innovation of the original turbine. The invention of microchip has led to innovations in many electrical devices. Similarly, the invention of fibre optics has resulted in innovations in communications, healthcare and power transmission. Unfortunately, the hazy border between invention, innovation and technology often makes it difficult to separate them. Indeed, these terms have been used interchangeably throughout the literature.

As mentioned before, an invention has a base technology, which is supported by complementary technologies. These complementary technologies are themselves made of core and other complementary technologies. If one further breaks down each one of these technologies in this structure, one would find that they are made of various knowledge elements. For example, the construction of a water reservoir requires the knowledge of dynamics of fluid flow, the knowledge of materials for building the reservoir, the knowledge of how these materials behave under the pressure exerted by the water etc. The knowledge elements could be in the form of scientific facts, procedures, experiences or any piece of information that could be useful in solving the related problem. Consequently, what emerges is a complicated network of knowledge elements that interact with each other at various levels together forming the technology. *Thus, the knowledge structure of an invention may be defined as a network of interdependent knowledge elements that are connected with each other due to the knowledge they share and together provide the means to achieve the purpose that is defined by the invention.*

In the knowledge structure of an invention, each of the complementary technologies has a unique task, which helps the base technology fulfil the ultimate need. Consider the example of an electric car, the invention of which dates back to 1834 (Teixeira et al., 2015). For the optimal performance of this invention, it needs to be supported by four different technologies; battery, electric motor, controller, and charger (Helmers & Marx, 2012). The battery stores and provides electricity, the motor controller governs the complete operations and distributes power and the electric motor converts the electrical energy to mechanical energy. The success of this technology weighs heavily on the efficiency of the charger and the capacity of the battery. The earliest batteries were heavy and low in capacity thus, seriously limiting the speed and range of these cars with an added inconvenience of requiring frequent recharge. Progress in battery storage technology has greatly improved the overall efficiency of the electric cars today. The charger is another crucial component of this set up (Helmers & Marx, 2012). The efficiency of the charger determines how fast the batteries can be recharged with minimal wastage of electricity. Hence if it takes many hours for the batteries to recharge due to the low efficiency of the charger, this would render the invention practically non-viable. The nascent stage of various technologies involved in an electric vehicle restricted its adoption in the initial years.

Thus, it can be seen that maturity of every supporting technology in the invention is highly important for the viability of the invention. The failure of any one technology would have a cascading effect on the whole invention. Therefore, when evaluating the technical value of an invention, one should assess the entire knowledge structure instead of the invention in isolation.

## 3.4 Structural Form

The existence of a structure prompts us to further define the structural form. Structural forms help us better understand the system. For example, biological classifications can be represented by a tree structure, which enables us to understand how different species evolved. Weather patterns can be represented by a ring structure. The work by Kuhn (1962) shows us that a structure exists underneath scientific revolutions. Kuhn described this structure as periods of conceptual continuity interrupted by scientific revolutions that lead to new paradigms. Inspired by this work, Dosi (1982) suggested a similar structure of technological paradigms and dominant technology. While research hints at the existence of a structure of inventions, its structural form has not yet been explored. The inherent difficulty in defining the structure of inventions is that inventions are a result of knowledge elements and research, which are intangible entities. Defining the relationship between these knowledge elements, which form the building elements of the structure, then becomes a difficult task. Also, since there are different ways to represent these knowledge elements, it may further result in different structural forms. For example, Dong and Sarkar (2015) use products' Function-Behaviour-Structure ontology to create the knowledge structure of inventions. On the other hand (von Wartburg et al., 2005) uses patents to represent knowledge elements and patent citations to create the knowledge structure. I shall discuss more about patent citation network-based knowledge structures in CHAPTER 4.

In order to understand the structural form, I first break down the structure into smaller units. Kemp and Tenenbaum (2008) observe that most of the structural forms are made of recurring units. When a patent citation network is used to represent the knowledge structure, the recurring unit is a tree form where the child nodes represent the citations of the parent node. This form is depicted in Figure 3-2. In this figure the arrows point to the direction of knowledge flow. Each child node then extends to include more child nodes. This unit keeps growing more generations, eventually forming the complete knowledge structure of the invention. This is a rather simplistic view of the knowledge structure but can be used as a foundation that can be further refined.

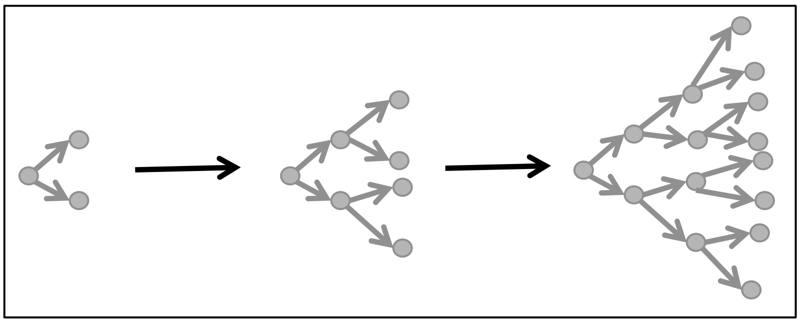


**Figure 3-2: Recurring tree form in knowledge structure**

When discussing structural forms, it is important to understand that the structural form of a system is a result of various factors affecting it. For example, the spiral shape of a DNA molecule is a result of the affinity or aversion of its constituents (sugar, phosphate and base) to water. The knowledge structure of an invention takes shape over time, amidst the various factors that influence it. The structural form should therefore, reflect those factors. However, before accounting for those factors, it is first important to define how the knowledge elements are traced and placed in the structure, as this determines the basic structure. In the following discussion I use the example of patent citation networks to form the basic knowledge structure of the invention. Other techniques, as Function-Behaviour-Structure ontology may also be used.

When patents are used to represent the knowledge elements, tracing their references can help draw the knowledge structure. References are the knowledge background of the invention that has contributed to the invention. The immediate references of a patent are called the first-generation citations. References of these references then form the second-generation citations, and so on and so forth. A reference could be a part of more than one generation of citation.

Hu et al. (2011) describe four different types of citation generations $G^s$, $H^s$, $G^m$ and $H^m$. The following is a brief overview of the generations, however I give a detailed explanation of the generations in CHAPTER 4 section 4.4.

The citation generations differ in terms of whether the generations overlap and/or the citations are repeated. Thus,

- Generation $G_n$ contains all publications that cite at least one generation $G_{n-1}$ publication and that do not yet belong to $G_k$, k=0, . . ., n−1.
- Generation $H_n$ contains all publications that cite at least one generation $H_{n-1}$ publication.

Generations of type $G_n$ are disjoint, while generations of type $H_n$ usually are not. The second distinction is between sets and multi-sets:

- A generation is a set (an element belongs to it or not, and this exactly once);
- A generation is a multi-set (an element may belong to it several times).

The choice of the generation depends on the kind of analysis being undertaken and the assumptions involved. For example, Atallah and Rodríguez (2013) chose $H^m$ type of generation in their analysis with the assumption that some patents have direct influence on some and indirect influence on other patents in the network. Hence their influence should be counted twice with appropriate weights.

I shall next present the knowledge structure based on two of these generation types; $G^s$ and $H^m$. These two generations represent two extreme ends of the generation types; i.e. neither the generation nor the citations are repeated in $G^s$ while in $H^m$ one may find repetition of both. To demonstrate the knowledge structure based on these two generation, consider the example of a target invention represented by patent P. TABLE 3-1 gives the details of the backward citations (references) of all generations for this patent. The first column shows all the references, which form the knowledge elements in the knowledge structure of patent P while the second column shows the generations in which they occur. The third column gives the year of application and the final column shows the technological sector that they belong to. References C, F, J and L appear in more than one generation while the remaining references appear in only one generation. The knowledge structure of patent P has 13 knowledge elements that belong to 4 different sectors and were created within a span of 70 years.

**TABLE 3-1: Sample invention P description**

| Year of Application of Patent P: 2001<br>Sector of Patent P: 1 | | | |
|---|---|---|---|
| **Reference** | **Generation** | **Year of Application** | **Sector** |
| A | 1 | 2000 | 1 |
| B | 1 | 1999 | 2 |
| C | 1,2 | 1945 | 1 |
| D | 1 | 1997 | 3 |
| E | 2 | 1995 | 1 |
| F | 2,3 | 1984 | 1 |
| G | 2 | 1985 | 1 |
| H | 2 | 1985 | 2 |
| I | 2 | 1989 | 3 |
| J | 3,4 | 1980 | 2 |
| K | 3 | 1985 | 1 |
| L | 4,5 | 1930 | 1 |
| M | 4 | 1960 | 4 |

I first investigate the knowledge structure of P through the patent citation network based on $H^m$ type of generation. Following this type of generation for forward citations, Atallah and Rodriguez observed that the citation distribution followed an inverter U shape. Bosworth (2004) predicted that tracing citations backwards in time will produce a monotonically increasing number of patents. However, Ellis et al. (1978) note that with increasing number of generations, few relevant patents are found. The reason for the difference between Bosworth and Ellis et al. observations could be the time span of the data being observed. Since Bosworth used US patent citations, the data of the study was limited to the mid-1970's. Hence, Bosworth could observe the backward citations up to 24 years (1976-2000) or five generations only. While the number of generations covered in Ellis et al. work is unclear, the authors claim to have continued the process until no new relevant patent was found. Thus, based on these observations, the knowledge structure of the invention would take the form of an "eye" as shown in Figure 3-3.

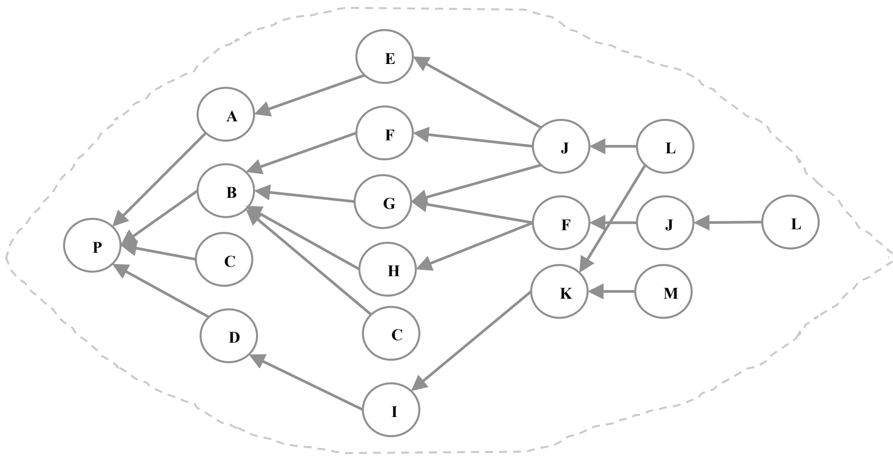



**Figure 3-3: Structural form of patent P based on $H^m$ type generations**

The vertical span of this structure gives us an approximation of the size of the knowledge base, while the horizontal span gives an insight into the age of the domain. For $G^s$ type of citation generation, the knowledge structure takes a similar form, as shown in Figure 3-4. However, as the number of overlapping references and generations increases, the structural form deviates from the recognizable "eye" form and takes the appearance of a tangled web.

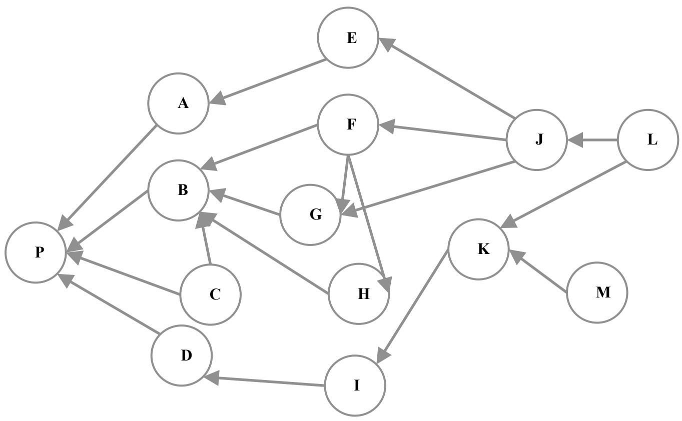



**Figure 3-4: Structural form of patent P based on $G^s$ type generations**

Having selected the appropriate generation type, the next step would be to form the basic structure. The basic structure should include all its essential characteristics. The age of the knowledge elements is one such characteristic. Scholars have studied inventions and conclude that knowledge both old and new, are essential in building an invention (Katila, 2002; Nerkar, 2003). Old knowledge is more legitimate and reliable while new knowledge reflects the current capabilities in the field. Thus, age of the knowledge is an important element that should reflect in the structure of the invention. While it is true that the horizontal span (geodesic diameter) of the knowledge structure as depicted by the $H^m$ generations gives an approximation of time, the scale of it cannot be considered linear as some of the citations are repeated. Thus, the knowledge structure of invention P ($G^s$ type of citation generation) takes the form shown in Figure 3-5 when one factors in the age of the knowledge. As it can be seen, the inherent difficulty in using citation data for the purpose of visualizing knowledge structure is that the structural form is dependent on how one traces the citations and places them in the structure. Adding the time factor to the knowledge structure, however, anchors its elements and provides a more concrete shape to work with.

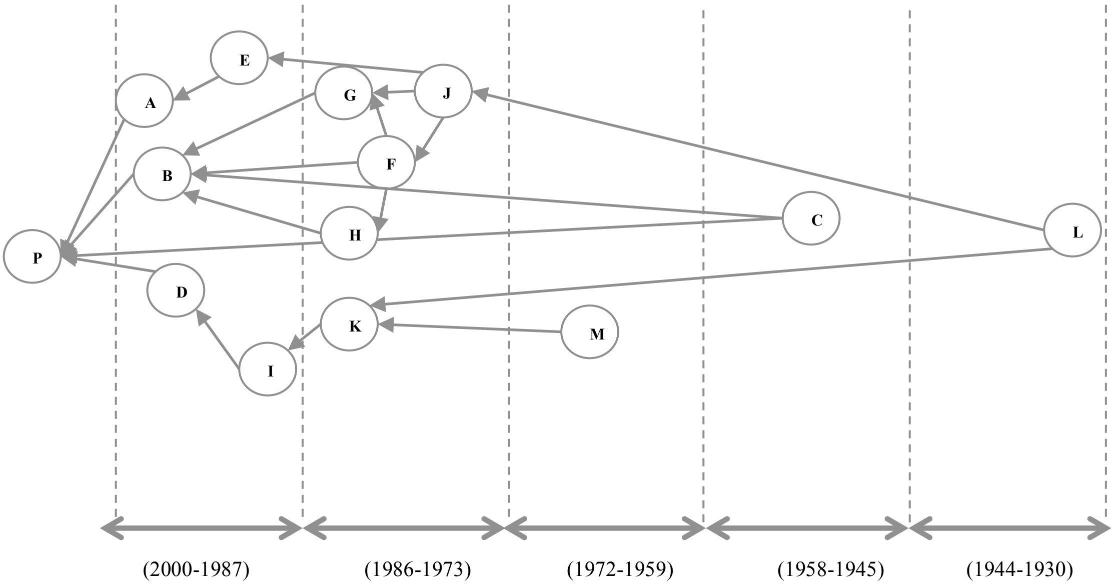



**Figure 3-5: Knowledge structure of patent P after factoring in age of the knowledge**

This forms the basic knowledge structure of the invention. To this structure, one can add more dimensions to factor in additional considerations. For example, the knowledge elements can be further segregated based on the sector they come from. It has been suggested that the combination of local knowledge leads to inventions that are a refinement of previous inventions while combination of distant knowledge leads to inventions that are more radical in nature (March, 1991). Fleming (2001) says that in inventions, combination of local knowledge is more certain and on an average leads to more successful inventions. By drawing knowledge from more familiar sources, an inventor is less likely to develop a completely useless invention. However, they also decrease the potential of developing a radically different invention that is of much greater impact. Fleming argues that inventions that incorporate familiar components should be more useful because inventors can select more appropriate components and can better predict the performance of the included components. Taking into account the sector of the knowledge elements, the knowledge structure then takes a form as shown in Figure 3-6. As the number of sectors and knowledge elements increases, this results in a much more complicated web.

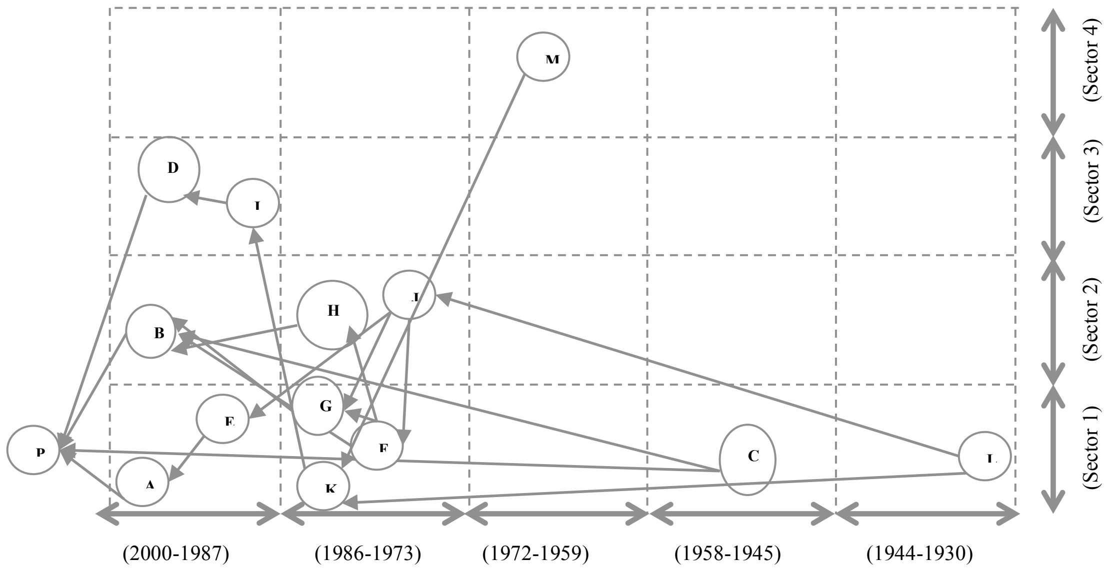



**Figure 3-6: Knowledge structure of patent P after factoring in age and sector of knowledge elements**

Similarly, one can take into account other factors such as the knowledge flow between the elements or value of the knowledge elements. As more factors are introduced, it becomes apparent that the knowledge structure assumes different forms based on those factors. The complex interplay of many factors involved in the knowledge creation process means that the structural form will not only vary from invention to invention but also for the same invention depending on which factors have been considered. In such a scenario the structural form itself may not be helpful in indicating the value of the invention. It is the characteristics exhibited by the structure that inform us whether the knowledge embedded in the invention is capable of delivering what it promises to deliver. Thus, I hypothesise that:

*HYPOTHESIS: The structural characteristics displayed by the knowledge structure of inventions with high technical value are different from those of inventions with low technical value.*

Inventions employing highly mature technologies result in successful products and also find application in future technologies, thus, registering a high technical value. Exploring the knowledge structure would help us identify inventions with viable technology amongst a cohort of inventions. I further explore two specific characteristics of the knowledge structure: knowledge accumulation and knowledge appropriation. In CHAPTER 5, I develop my theory on why knowledge accumulation and knowledge appropriation of the knowledge structure could be suitable indicators of the technical value and also explain how they may be measured.

## 3.5 Summary

The first and foremost step in technology forecasting process is understanding the maturity of the technology. A good assessment at an early stage leads to informed decisions on the allocation of funds and resource, reduced risk in investment opportunities and achievable technology commercialization plans. Technological maturity may be defined as the stage in the progress of a technological field, when most of the technical challenges posed by the sector have been resolved and the technology successfully results in products. An invention with mature technology would hold a higher technical value than an invention whose technology has not yet reached maturity.

In this research I propose the use of the characteristics displayed by the knowledge structure as an indicator of technical value. Studies have shown the importance of prior knowledge and the knowledge structure in the progress of technologies. Thus, the characteristics of the knowledge structure of an invention may be an important indicator of the value of its underlying technology. The knowledge structure of an invention is made of a network of knowledge elements that make up the base and complementary technologies. In this intricate and interwoven structure, the elements borrow knowledge from each other and are dependent on each other for their success. Failure of one technology in this structure would affect the overall maturity of the invention. Therefore, one should assess the entire knowledge structure in order to assess the technical value of the invention.

# 4 PATENT CITATION NETWORK

## 4.1 Introduction

In the last chapter I discussed about the differences in the knowledge structure of inventions. Characteristics displayed by a knowledge structure could potentially be the value indicators. The idea however, is to be able to predict the technical value at the earliest possible incidence. The question then arises; what types of knowledge structures allow us to predict the value of inventions?

Patent data provide a unique opportunity to view the knowledge structure of inventions, due to the depth of information they carry. Even though the limitations of using patent indicators for assessing patent value have been raised, (Reitzig, 2004a; van Zeebroeck, 2011; van Zeebroeck & van Pottelsberghe de la Potterie, 2011), the increasing number of studies in this domain point to the fact that patents can be valuable sources of information that can help us understand inventions and their knowledge structure. In this chapter, I discuss patent citation networks, and how they may be ideal for representing the knowledge structure of inventions.

## 4.2 Representing the knowledge structure of inventions

The term "knowledge structure" is commonly used in the literature to describe the evolution and growth of different branches of science. Studies such as those by Gu et al. (2017), Su and Lee (2010) and Samiee and Chabowski (2012) used bibliometrics along with visualization techniques to achieve this. Such studies serve as guidelines for future research. One may find that the terms "knowledge structure" and "knowledge network" are often used interchangeably in the literature. Phelps et al. (2012) describe a knowledge network as a set of knowledge elements that transmit and create knowledge and are interconnected by social relationships. The authors further define knowledge elements as those embodied in discrete artefacts (such as patents, papers and products) or non-human repositories (such as databases or catalogues) or individuals and higher collectives (such as teams and organizations).

When the knowledge elements are individuals or groups, the resulting knowledge network describes how collaborations affect knowledge creation and its flow. When the knowledge elements are organizations, the knowledge network describes the absorptive capacity of a firm. For example, Bell and Zaheer (2007) studied the organizational network of Canadian mutual fund companies to understand the influence of geography on knowledge flow. The study concluded that institutional-level ties are valuable in knowledge transmission only when such ties are geographically proximate. The study also concluded that geographically distant individual-level ties are good conduits of knowledge flow. Balland and Rigby (2016) created a bipartite network between cities and technologies to study how spatial diffusion of knowledge is related to its complexity. Their analysis revealed wide geographical variations in knowledge complexity. The authors also concluded that complex knowledge resists diffusion. Using a collaboration network of inventors in German biotechnology, Ter Wal (2014) showed that the geographical proximity between inventors is mostly relevant for tie formation in the early stage of the industry when its knowledge base is mostly basic. Knowledge structures depicted in such studies account for the complete knowledge possessed by an individual or an organization that could have led to the creation of multiple inventions/innovations. Assessing the value of a single invention from this cohort then becomes challenging. To predict the value of a specific invention, one should only take into account the knowledge elements that have contributed directly or indirectly to the creation of that specific invention. Such information would be available through knowledge artefacts such as patents and papers.

Thus, the structural analysis of a network based on patents or papers should reveal the technical value of the invention. Analysis of such networks either follows bibliometric techniques or content-based techniques. Content-based analysis uses text-mining techniques such as text segmentation, summary extraction, and co-word analysis to detect technological trends (e.g. see (Gerken & Moehrle, 2012; Tseng et al., 2007; Yoon et al., 2011). Bibliometric approach uses statistical and mathematical models to analyse value through indicators such as citation counts (Carpenter et al., 1981; Verspagen, 2007). In the case of patent networks, indicators such as claims (Baron & Delcamp, 2011; Lerner, 1994), patent life (Bessen, 2008b), family size (Harhoff et al., 2003; Sternitzke, 2009), processing time (Lin et al., 2007) and other metrics are also utilised in assessing the technical value. Text mining based techniques are complex due to the unstructured and fuzzy nature of natural language (Sailaja et al., 2016). This is further complicated by the fact that many patents are described in languages other than English, which would necessitate a further translation. Thus, the use of this technique as a tool for technology management purpose may be impractical.

At this point it is important to highlight the difference between papers and patents. Journal articles (papers) are associated with scientific knowledge while patents represent the practical implementation of that knowledge, that is, inventions. The references given in these documents are windows to the knowledge foundation of the invention/science and therefore, can help us build the knowledge structure of the invention. It is however, important to note that the motivation behind citing in a journal article is much different from that in patents. Meyer (2000) notes that some of the reasons for citing in journal articles include criticizing pervious work, correcting one's own work, paying homage to pioneers and disputing claims of others. Knowledge elements from such citations may not have any contribution towards the actual invention in question and hence their presence in the knowledge structure is of little significance. Patent citation networks are therefore better suited for exploring the knowledge structure of inventions.

## 4.3 Patent Citation Network

With the understanding that patent citation networks are sufficient to represent the knowledge structure of inventions, I then further explore these networks. It is observed that analysis of patent citation networks is conducted either on full networks (Choe et al., 2013; Fontana & Nuvolari, 2009) or on ego networks (Atallah & Rodríguez, 2013; Bosworth, 2004; Ellis et al., 1978; Hu et al., 2012). Full networks take an overall perspective of the network while the ego networks focus on the ties that affect a particular patent. Ego patent citation networks, both in the forward (based on forward citations) and backward (based on references) directions have been well studied. When a patent cites another patent, it indicates that the citing patent is based on knowledge that was developed by the cited patent. Tracing these citation links leads to a network that gives us a macroscopic view of the developments in the technology. In the forward direction, the network consists of the focal patent and all the patents that cite it directly or indirectly. An indirect citation means that two patents are connected together through one or more intermediate patents in the network. A forward facing ego-citation network can be seen in the works of Atallah and Rodríguez (2013). The authors describe the analysis in their work as "indicative of the impact of that patent through time". Thus, a forward facing ego network would show the impact of the invention on successive technologies. On the other hand, backward citations show the knowledge roots of the technology. For example, Ellis et al. (1978) carried out an exploratory study to assess the usefulness of patent citation networks in mapping the history and identifying key turning points in a technological field. The authors studied the key developments in five subject areas: electrophotography, semi-synthetic penicillin, tobacco substitutes, Ziegler-Natta catalysis and hovercraft. The authors traced the references of 5 focal patents to achieve this aim. In the process the authors demonstrated the usefulness of patent citation networks in understanding the technological developments of a field. Similarly Verspagen (2007) traced the backward citations of patents in fuel-cell technology to identify the main paths of technological developments in this sector. The knowledge structure of an invention should include its knowledge roots that have contributed towards the invention.

Another important point to note is that the knowledge structure of an invention should include all the knowledge elements that have contributed directly and indirectly towards the creation of the invention. In a patent citation network this is visible through multiple-generation references of a patent. Multiple-generation citations are references of references and have also been termed as "indirect citations" (Atallah & Rodríguez, 2013) and "multiple-round citations" (Bosworth, 2004). Scholars (Hu et al., 2012; Rodriguez et al., 2015; von Wartburg et al., 2005) have argued that multiple-generations of citations provide a better picture of knowledge flow and the technological developments that have led to the invention. Very few studies have included multiple-generation citations in their analysis of the knowledge structures. These studies, amongst other things, differ in terms of "how much" of the knowledge structure is included in the study. This is depicted in Figure 4-1. For example, Trajtenberg (1997) measured the value of an invention based on the importance of its knowledge base. The author used the immediate references of the patent as its knowledge base. Hu et al. (2012) included two generations of references to include the influence of technological complexity on the value of the invention. Bosworth (2004), on the other hand, included many more generations of references in his study to demonstrate that such structures can be used to explore the ancestral roots of a patent. Ellis et al. (1978) drew out a similar patent citation network to study the important milestones in a technological field. It is unclear how many generations of citations were included in their study. Marra et al. (2015) state that, "examining patent citations over several generations could enrich our understanding of citation network dynamics". Therefore, a partial structure may not provide a complete view of the influencing factors of patent value. *Thus, an ego citation network based on multiple-generation backward citations would reveal the knowledge structure of the invention.*

My research considers the complete knowledge structure of the invention by including all the generations of references in evaluating the patent value.

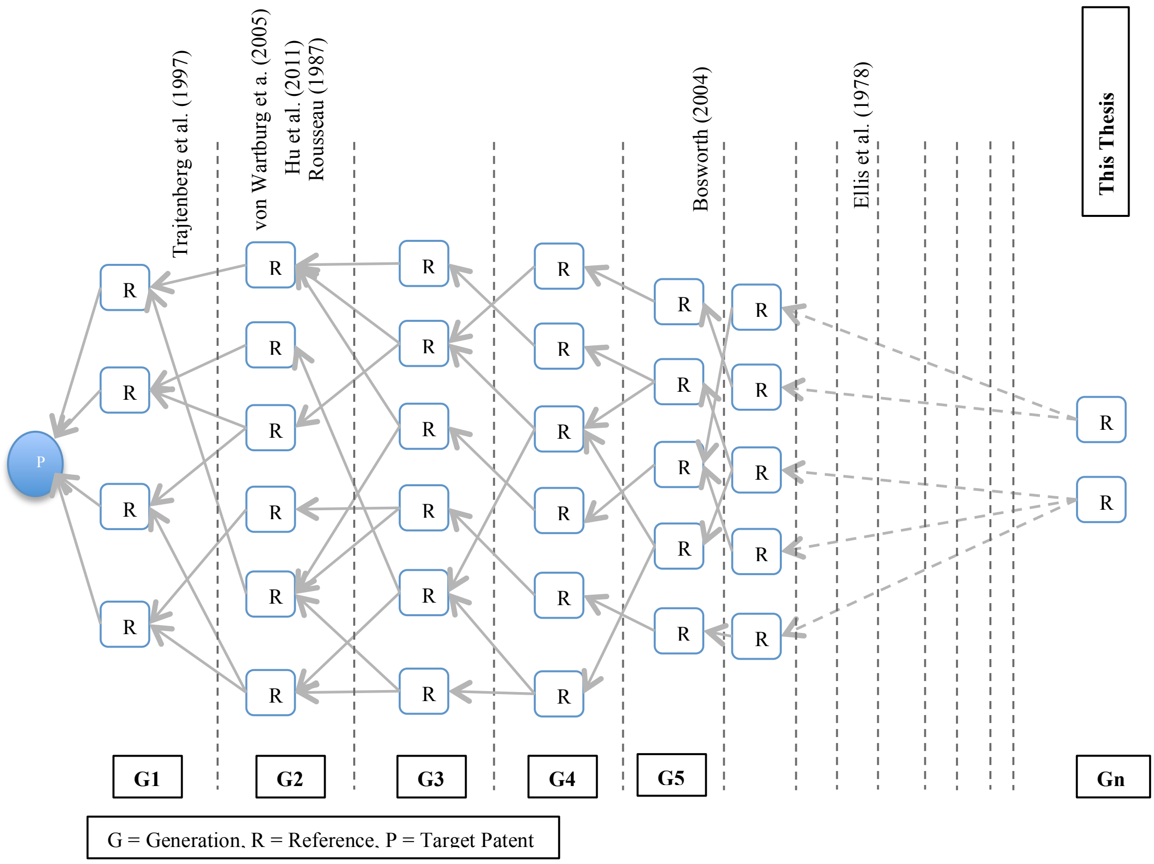



**Figure 4-1: Generations of references used by different studies**

## 4.4 Features of a patent citation network

With the claim that a backward-facing ego-citation network that includes all the known generations of citations, best represents the knowledge structure of an invention, I then examine the finer details of the knowledge structure. In a patent citation network, the immediate references of a patent that form its first-generation citations are considered to have a direct influence on the patent. The indirect citations occur from the second generation onwards, that is; references of references. It is common for a reference to occur in multiple generations, which necessitates the question; should its influence be counted once or more? The answer to this question lies in the assumptions of the analysis model. For example, Atallah and Rodríguez (2013) argue that some patents have a direct as well as indirect influence on the focal patent. In such cases it is reasonable to count their effect twice. Marra et al. (2015) argue that patent citations are measures of knowledge flow and thus counted a citation only once at their first appearance.

Depending on how a researcher wishes to perform the analysis, Hu et al. (2011) proposes four different types of citation generations to choose from; $G^s$, $G^m$, $H^s$ and $H^m$ . These generations have also been discussed briefly in section 3.4 of CHAPTER 3. These generations differ in terms of whether or not the generations overlap and how many times an element is counted. If the subscript n denotes the generation;

(1) Generation $G_n$ contains all publications that cite at least one generation $G_{n-1}$ publication and that do not yet belong to $G_k$, k=0, . . ., n−1.

(2) Generation $H_n$ contains all publications that cite at least one generation $H_{n-1}$ publication.

The superscripts *s* and *m* denote set and multiset. A generation is a set if an element belongs to it only once while if it is a multiset an element can belong to it several times. For more clarity, consider the generation structure of target set [a,b] as given in Figure 4-2.

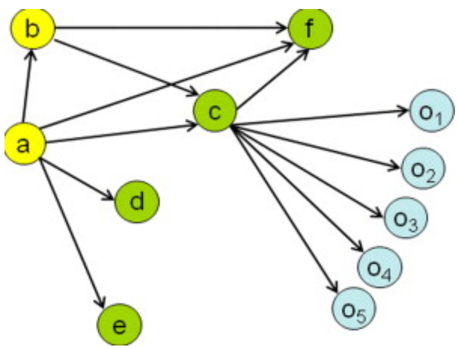



**Figure 4-2: Generational Structure from Hu et al. (2011)**

Thus, in reference to citation network in Figure 4-2, the authors define the generations in the following way. For target set [a,b], different generation sets would comprise of:

| | | | |
|---|---|---|---|
| $G_0$=[a,b]<br>$G_1^s$= [c,d,e,f]<br>$G_2^s$ =<br>[$o_1$,$o_2$,$o_3$,$o_4$,$o_5$] | $H_0$=[a,b]<br>$H_1^s$= [b,c,d,e,f]<br>$H_2^s$ =<br>[c,f,$o_1$,$o_2$,$o_3$,$o_4$,$o_5$]<br>$H_3^s$ = [f,$o_1$,$o_2$,$o_3$,$o_4$,$o_5$] | $G_0$=[a,b]<br>$G_1^m$= [c, c, d,e,f]<br>$G_2^m$ =<br>[$o_1$,$o_2$,$o_3$,$o_4$,$o_5$] | $H_0$=[a,b]<br>$H_1^m$= [b,c,c,d,e,f,f]<br>$H_2^m$ =<br>[c,f,f,$o_1$,$o_2$,$o_3$,$o_4$,$o_5$,f,$o_1$,$o_2$,$o_3$,$o_4$,$o_5$]<br>$H_3^m$ = [f,$o_1$,$o_2$,$o_3$,$o_4$,$o_5$] |

This nomenclature is valid for both backward and forward citations. The authors further demonstrated that the value of the influence of indirect citations varies depending on how one chooses to define these generations. Based on this definition, it can be seen that Atallah and Rodríguez (2013) adopted $H^m$ type of generations while Marra et al. (2015) use $G^s$ type of generations. My research adopts $G^s$ type of citations for the analysis of patent citation network. Also, the authors, Hu et al. (2011), indicate that the target set could be a set of documents, such as all the patents granted to an organization. In my research, the target set is a single patent.

Once the generation type has been chosen, the next question to be tackled is the manner of treating the indirect citations. The direct citations have been considered to be more influential than indirect citations. For example, in a study of patent citation networks in the radio frequency identification technology, Hung and Wang (2010) observe that a few critical patents may affect many other patents and thus, dominate the development of key technologies. In an ego citation network, this may imply that few patents have a greater contribution towards the creation of the invention than others. This understanding is crucial while factoring in indirect citations for patent evaluations. Since the contribution of knowledge elements towards the creation of an invention varies, they should be weighted appropriately during patent value assessment. Atallah and Rodríguez (2013) decrease the weight of citations from farther generations. Trajtenberg (1997) adopts a similar strategy and introduces a "discount factor" in their patent value indicators, aimed to down-weight the second generation. In my research the weight of the citation is based on the age of the patent being cited. Scholars (Karlsson & Åhlström, 1999; Nerkar, 2003) have proposed that age of the knowledge is an essential factor that may have an effect on the technical value of inventions. Older knowledge may be considered to have a weaker influence on the invention, as inventors tend to build more on new knowledge.

## 4.5 Summary

The discussion so far may be summarized in the following manner. Ego patent citation networks based on backward citations are sufficient to represent the knowledge structure of an invention. A few scholars have successfully demonstrated the use of such citation networks in exploring the technological roots of an invention and identifying important technological milestones in a domain. However, studies that demonstrate patent valuation techniques based on backward facing ego citation networks (ego citation networks tracing references) are still limited. The position of a patent within its ego citation network has been shown to be an indicator of its value. Many studies have concluded that, one should also consider the effect of indirect citations in order to get a better understanding of the impact of a patent. To take into account all the indirect citations, one would thus, need to include all the generations of references. None of the studies have yet demonstrated methodologies employing all the generations of references for evaluating technical value of a patent. Moreover, patent valuation techniques that do consider the knowledge base of an invention do not take into account the age of the knowledge. In order to fill these shortcomings, I create the knowledge structure by drawing a ego patent citation network based on references. In order to take into account the complete knowledge structure, I use all the available generations of references. Also, I take into account the age of the patents while assessing the value of the patent.

# 5 STRUCTURAL CHARACTERISTICS

## 5.1 Introduction

In the last two chapters I discussed the existence of knowledge structure of inventions. This knowledge structure could be disclosed through patent citation networks. Based on the technique used and how the knowledge elements are traced and identified, the knowledge structure could take different forms. In such a scenario, it is the characteristics displayed by the knowledge structure that could give us an indication of the technical value of the invention. In this chapter I explore two such characteristics of the knowledge structure: knowledge accumulation and knowledge appropriation. In the first part of this chapter, I examine accumulation of knowledge in the knowledge structure and develop my hypothesis on how it is indicative of the technical value. The second half of the chapter examines knowledge appropriation in inventions and a technique that can be used to measure it.

## 5.2 Knowledge Accumulation

Knowledge accumulation may be defined as the collective body of knowledge existing in a sector, which is a result of the efforts of many scholars striving to find answers to the various questions posed by the sector. Researchers have highlighted the importance of knowledge accumulation through various studies. For example, Lichtenberg (2013) hypothesized that increased research in biomedical field has yielded substantial improvements in longevity and health of humans. The author used publication counts in the field as evidence of knowledge accumulation and found that it had a strong inverse relationship with the mortality rate. Evenson and Kislev (1973) studied agriculture production and found a positive correlation with the research output in the sector. Adams (1990) argues that technical change, growth in R&D and input growth can all be traced to accumulation of knowledge. Organizational level studies have shown that the knowledge base of an organization is related to its innovative productivity (Forés & Camisón, 2016). Research has also shown that accumulated knowledge stock has a positive effect on new knowledge creation. In short, knowledge accumulation has been associated with growth in many fields.

It is also well understood that new inventions are dependent on older inventions in more ways than one. They draw knowledge from them, build upon them or improve upon them. At times they need the technology from older inventions to complement their own. Technologies from older inventions may become integral part of a new invention or just support them. Thus, every invention is critically dependent on earlier work in order to achieve its goals. Many scholars have commented on the importance of prior knowledge in the creation of inventions. TABLE 5-1 gives a snapshot of some of the often-discussed work in this area. Researchers claim that inventions are a result of novel combinations of conceptual and/or physical materials that already exist in the domain (Fleming, 2001;

Nelson & Winter, 1982). Thus, simplistically speaking, inventors take up either an existing invention or technology, apply their new idea to it and create a new invention. The steam engine may be considered as a classic example of this. While James Watt receives much of the credit for the invention of steam engine, in reality its development was an outcome of efforts made by hundreds of scientists and engineers over many decades (Kerker, 1961). The following are some of the key developments that show how the knowledge is linked together:

- Giambattista dell Porta (1606) – Demonstrated that steam could be used to move water.
- Denis Papin (1670) – Created an engine, which drove out the air from a cylinder by exploding gunpowder inside it. Papin later improved the model to be used with steam.
- Thomas Newcomen (1712) – Improved Papin's design to develop a practical steam engine.
- John Smeaton – Made improvements to the seal thus, tripling the efficiency of steam engine.
- James Watt (1765) – Using his knowledge of elasticity of steam at various temperatures, Watt added a separate condenser thus, making efficient use of the steam.

Porta's knowledge of steam helped Papin's rudimentary engine to function, which later gave birth to Newcomen's steam engine. Newcomen's design would not have existed in the first place had it not been for the inputs given by Papin and Porta. Much credit goes to all these engineers and scientists in eventually shaping James Watt's steam engine. Even disruptive technologies, which are believed to cause major paradigm shifts or even create new ones, have their foundation in old knowledge.

**TABLE 5-1: Studies highlighting the importance of prior knowledge in the creation of new knowledge.**

| **Main Findings** | **Reference** |
|---|---|
| Innovation combines components in a new way, or that it consists in carrying out new combinations | Schumpeter (1939) |
| The creation of any sort of novelty in art, science or practical life consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence | Nelson and Winter (1982) |
| Invention can be defined as either a new combination of components or a new relationship between previously combined components | Henderson and Clark (1990) |
| Knowledge in the form of methods, procedures, experiences of success and failure come together to form a technology | Dosi (1982) |
| Prior knowledge is worked upon and perfected to create new knowledge | Nerkar (2003) |
| A technological invention can be seen as the outcome of a recombination of existing knowledge | Fleming (2001) |
| Knowledge base of an organization is related to its innovative productivity | Ahuja and Katila (2001) |
| The main driver of the invention process is the novel combination of previously existing technologies. | Strumsky and Lobo (2015) |
| Invention as a process of linking some purpose or need with an effect that can be exploited to satisfy it. This involves the creation and combination of suitable working parts and supporting technologies. | Arthur (2007) |
| Invention mainly involves the combination and recombination of previously existing technological capabilities rather than the development of totally new capabilities | Strumsky et al. (2012) |

While it is easier to note the contribution of a specific prior invention/knowledge in triggering a new invention, the role played by the accumulated knowledge of the sector may be less obvious. As research progresses in a sector, it results in new findings, fresh theories and increased stories of success and failure. Inventors take inspiration from these findings directly or indirectly. They use these findings in their creations thus, adding to the existing knowledge in the domain. All this knowledge accumulates in the sector over time and together solves the technical challenges posed by the sector. Studies that trace the key developments of a technology field give evidence of the knowledge accumulated in the sector. For example, Fontana and Nuvolari (2009) showed that the success of Ethernet lay in the coming together of various technologies; coaxial cables, bus topology, packet switching, layering and network interface. Similarly Verspagen (2007) mapped over hundred years of development of fuel-cell technology to show the key developments. While the aim of the study by Verspagen (2007) was to explore the various technological trajectories, the knowledge accumulation, which resulted in these trajectories, is clearly visible. Literature is rich with such studies across all domains (Calero-Medina & Noyons, 2008; Cooray, 1985; Hummon & Dereian, 1989; Lin et al., 2011). These examples show that behind every invention exists a vast body of knowledge that had accumulated over time.

### 5.2.1 Knowledge accumulation and technical value

The discussion so far points out that knowledge accumulated in a sector can be associated with the progress of various aspects of the sector. Also, knowledge accumulation plays an important role in the creation of inventions. Armed with this information, I then look for a connection between knowledge accumulation and the technical value of inventions.

The value of an invention depends on the growth stage of its technology. A technology at its infancy has fewer practical applications and hence may not be considered valuable. Whereas, a technology that has attained maturity finds implementation in products and other successive technologies, thus, making it valuable. Beierlein et al. (2015) argue that knowledge accumulated in the sector is an important factor that determines its technological maturity. Based on this assumption the authors studied the technological state of Alzheimer disease drugs research. The results of their research imply that unless technologies attain maturity they do not result in successful products. Other studies in field of biomedical research observe similar findings (McNamee & Ledley, 2013; McNamee & Ledley, 2012). Technology growth curves are often used to depict the knowledge accumulated in the sector and estimate the developmental stage of the technology. Details on technology growth curves were discussed in section 2.2.4 of CHAPTER 2. Studies such as those by Beierlein et al. (2015), McNamee and Ledley (2013), McNamee and Ledley (2012), Beierlein et al. (2017), Christensen (1992a) and Yoon et al. (2014) have used the S-curve to determine the growth stage of various sectors. The bibliometric approach adopted in these studies uses cumulative publication counts as a proxy for knowledge accumulation.

Technological growth curves are quite useful in understanding the growth stage of the whole sector. However, application of them in assessing the value of specific inventions suffers the following disadvantages:

a. When using the technology growth curves to assess the maturity of individual inventions, forecasters work with the assumption that if the technology of the domain has reached maturity, then any individual invention incorporating that technology too would have attained technical maturity. This may be a highly optimistic assumption as inventions differ in their technological make up even if they achieve the same end task. For example, the domain of photovoltaic cells is made of different technology routes such as thin-film, multicrystalline cells, crystalline Si, organic cells etc., that have evolved over time. These technology routes differ from each other in terms of materials and/or the techniques used. Each technology route can be further split up into more routes based on the techniques or the materials being employed. Thus, an invention based on DSSC (dye-sensitized solar cell) technology is different in its technological make up from an invention based on thin-film photovoltaic technology even though both the technologies convert solar energy into electrical energy.

b. The growth slowing point (as measured in terms of knowledge production) on the growth curve is considered as an indication that the technology has attained maturity. However, for new technologies, it is difficult to judge whether or not the knowledge production has reached its slowing point. Slowing of knowledge production could also be a result of other external factors such as economic recession, change in national policies or simply lack of funding. For example, Filippetti and Archibugi (2009) observe that the economic recession of 2007-2008 resulted in decrease in investments in innovation across Europe. With so many factors involved, assessing technological maturity becomes a complex puzzle in itself. While the maturity of a technology is clearly visible through the growth-curve in retrospect, it is actually a dynamic phenomenon from a managerial perspective (Christensen, 1992a). Thus, growth-curves alone do not provide the complete picture.

c. An important aspect that is disregarded in the growth curves is the age of the knowledge. Though the horizontal axis of the growth curves is a time measure, it has little relevance to the age of the knowledge used in an invention. Nerkar (2003) showed that it is important that both old and new knowledge are applied toward the target patent, though. The author argues that recombining knowledge from broad time periods enables uncovering of valuable knowledge that is forgotten or whose time has not come yet. Age of the knowledge indicates that it has had the time to be tested and perfected. Also, a study by Karlsson and Åhlström (1999) showed that technologically more advanced products take a longer time to develop. The authors argue that product development activities often encounter technological uncertainties. Time is needed to digest and analyse these technological problems and ensure that correct solutions have been integrated. Nonetheless, it is generally true that age of the knowledge preceding an invention is an essential factor that may have an effect on the technical value of inventions.

The above discussion highlights that the technical value of an invention cannot be directly observed but may be inferred through the knowledge accumulation that has led to the invention. It should however, be noted that when knowledge accumulation is used to assess a technology, one is essentially measuring the "quantity" of knowledge produced in the sector. In some sense there is an underlying assumption that more research will lead to a mature technology. While intuitively this may sound reasonable, applying this concept to assess the maturity of technology in specific inventions has its challenges, the reason being that the amount of knowledge in any domain will always increase with time. By that virtue, newer inventions will always display a higher amount of knowledge accumulation. Thus, if one compared two inventions from different time periods, based only on knowledge accumulation in the sector, the newer invention would always appear mature and therefore, more viable than the older invention.

The discussion in the previous chapter showed that inventions are made of a complex network of knowledge elements that form the knowledge structure of the invention. Failure in performance of any knowledge element in this network would have a cascading effect in the knowledge structure and eventually on the performance of the invention. Hence, I argue that when it comes to assessing the technical value of individual inventions, one should consider the accumulation in the knowledge structure of the invention and not the technology sector on the whole. Accumulation of knowledge in the knowledge structure of an invention is indicative of the methods, procedures and efforts that have taken place to bring that specific invention into existence. The age of the knowledge, which is an integral part of this structure, reveals the research efforts, both direct and indirect that have contributed towards the invention. A higher knowledge accumulation behind the invention indicates that the invention has incorporated a higher amount of knowledge available in the sector. Thus, this leads to my hypothesis:

*HYPOTHESIS 1A: The knowledge accumulation in the knowledge structure is positively correlated to the technical value of the invention.*

## 5.3 Knowledge Appropriation

"A much remarked property of knowledge as an economic good is that it is capable of spillover" (Zucker et al., 2007). Knowledge spillover refers to the external benefits from knowledge creation that is enjoyed by parties other than the party investing in the creation (Agarwal et al., 2010). Economic growth at both regional and national level has been attributed to knowledge spillovers (González-Pernía & Peña-Legazkue, 2015; Lee, 2009; Sanchis et al., 2015). The performance of a firm has been known to depend on its ability to absorb knowledge spillovers. Firms assimilate knowledge spillovers to create new knowledge and apply it to commercial ends. A firm's ability to do so is termed as its absorptive capacity (Cohen & Levinthal, 1989). In order to absorb knowledge spillovers, organizations invest in R&D, which further develops their absorptive capacity (Cohen & Levinthal, 1989, 2000;

Kostopoulos et al., 2011). Cohen and Levinthal (2000) argue that the absorptive capacity of an organization will depend on the absorptive capacity of its individual members. Tseng et al. (2011) show that innovations can be stimulated by increasing the firms' capacity to absorb knowledge spillovers. In short, knowledge spillover is at the heart of growth at regional, national, organizational and even individual level. With this understanding, studies have focused on the nature of knowledge spillovers and factors that affect them. For example, it is known that knowledge spillovers tend to be localized geographically, though localization fades slowly with time (Audretsch & Feldman, 1996; Jaffe et al., 1993). Complex knowledge spills slower than simple knowledge (Balland & Rigby, 2017; Thomas & Zaytseva, 2016). Knowledge flowing from beyond the organizational and technological boundaries results in a stronger impact on subsequent technological evolutions within a domain or organization (Rosenkopf & Nerkar, 2001).

In developing the concept of absorptive capacity of a firm, Cohen and Levinthal (1989) turn to cognitive science to explore how individuals acquire new knowledge. Learning is the acquisition of knowledge whereas memory is the ability to recall that knowledge and utilise it. Learning and memory are closely related concepts. Studies in the area of cognitive and behavioural science suggest that human memory is assortative in nature. This implies that humans remember a new piece of information by associating it with previously acquired knowledge that is already embedded in the memory. Such linkages help individuals make sense of the new knowledge. The more extensive the existing knowledge in the memory, the higher is the probability of forming associations with the new knowledge. Therefore, the accumulated prior knowledge of an individual increases both the ability to acquire new knowledge and recall and use it.

In the domain of innovations, these linkages appear in the form of interactions and collaborations. Active knowledge exchanges between firms, academic institutions and government bodies lead to a healthy environment for innovations to develop (Etzkowitz & Leydesdorff, 2000). Huggins and Johnston (2010) state that a key determinant of regional innovation and growth differential is the capability and capacity of entrepreneurial firms to establish the network capital. The authors define network capital as consisting of investments in strategic and calculative relations with other firms and organizations in order to gain access to knowledge to enhance expected economic returns, primarily through innovations. The role played by knowledge flow between individuals and organizations, in the process of innovation, is a highly explored subject. Knowledge spillover studies attempting to understand the causal relationship between knowledge flow and inventions either focus on the format of knowledge being transferred or on the path of the knowledge flow. The former group investigates how different formats of knowledge affect its flow. Knowledge format describes the features of the knowledge such as its sector (Choe et al., 2013; Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001), complexity (Balland & Rigby, 2016; Lang et al., 2014; Thomas & Zaytseva, 2016) and basicness (science) (Agrawal & Henderson, 2009; Bacchiocchi & Montobbio, 2009; Lööf et al., 2008; Ozel, 2012; Sorenson & Fleming, 2004). The latter group explores how different types of knowledge flow paths affect the flow itself. These paths are the ties between the knowledge seeker and knowledge facilitator, such as social ties (Bell & Zaheer, 2007), collaborations (Gertler & Levitte, 2005; Huggins & Johnston, 2010), institutional ties (Gittelman, 2006) etc.

Let us now examine the effect of knowledge spillovers from the perspective of individual inventions. During the inventing process, inventors turn to the knowledge accumulated in the sector for potential solutions or inspirations to solve specific problems associated with the invention. The solution can be in the form of a collaborating partner or existing knowledge. This solution may come either from sectors close to the inventors' sector or from further away sectors. Out of a gamut of possible solutions, the inventor choses the one that best compliments his/her own knowledge base and/or technological competency (Dong & Pourmohamadi, 2014). This ensures efficient knowledge transfer and knowledge integration (Lakemond et al., 2016). When the inventor finds a suitable supporting technology, a knowledge flow link is formed between the knowledge provider and the knowledge seeker indicating that knowledge has been appropriated from the sector. Since every piece of knowledge is built on prior knowledge (Dosi, 1982), the inventor also appropriates knowledge indirectly from a wider segment of the technology domain. In a well-connected sector, the inventor would be able to appropriate more knowledge from the sector as compared to a sector with fewer knowledge spillovers. Tracing the knowledge flow pathways should therefore reveal how much knowledge of the sector has been appropriated by an inventor in creating an invention.

One of the ways to visualise and examine the knowledge appropriated from a technological domain is through a patent citation network. Patent citation networks represent the knowledge network of technological domains. Knowledge networks take shape over time as a result of active research and provide solutions to various technological problems in the sector. This is achieved largely through knowledge spillovers. The mechanism of knowledge spillover leaves traces in the form of citation (Jaffe et al., 1993). When a patent cites another patent, it indicates that the citing patent to some extent has appropriated knowledge from the cited patent. Thus, citation link is an evidence of knowledge appropriation. It is in fact possible to trace the knowledge appropriation that has led to an innovation (patent) through its backward citations (references). This perspective is taken in the work of Ellis et al. (1978), Bosworth (2004), von Wartburg et al. (2005), Hu et al. (2012) and other scholars.

The knowledge network of a technological domain, as represented by its patent citation network, holds a vast amount of information. The density of this network in terms of number of patents informs us of the research activities and knowledge accumulation in the sector. The citation links in this network illustrate the efficiency of knowledge flow (Goel et al., 2016; Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001; Sorenson et al., 2006). The topology of this network allows us to understand how knowledge flow shapes the technological domain. For example, Wang et al. (2017) noted that increasing the heterogeneity of the network improves knowledge spillovers. In a study comprising citation network of 6708 journal articles, Massimo (2012) notes that the citation network represents a small world network. The author concluded that this indicates a highly efficient knowledge flow within the technological domain and the research community. Similarly, Weng and Daim (2012) explored how being in a core or peripheral position within a technological network affects the contributions of an invention in shaping the future technological developments. Thus, it is apparent that the mechanism of knowledge spillovers create structural characteristics in the network in which inventors operate. These structural characteristics are observable, thus, allowing us to understand knowledge flow and make strategic decisions to enhance it within the network.

### 5.3.1 Measuring Knowledge Appropriation

Konno (2016a) argues that the knowledge spillover process proceeds over a structure that can be expressed as a network. Knowledge spillovers have been extensively studied through network structures. The majority of these studies have primarily focused on collaboration networks to investigate the spillover effects. For example, Wang et al. (2017) examined the role of collaboration strength in enabling knowledge spillovers. The authors observed that sector specific technology spilled more efficiently through weak ties. Konno (2016b) notes that with the increasing heterogeneity of the collaboration network, the likelihood of firms undertaking R&D increases, in turn increasing their growth rate. The author argues that the increase in heterogeneity of the network is caused by an increased degree of hub vertices. Such vertices are sources of knowledge spillover. Other examples include studies by Graf (2012), Guan et al. (2016), Liang and Liu (2018) and many more.

To assess how much knowledge has been appropriated by an invention, one would need to examine the knowledge flowing to the invention from all the knowledge elements in the network. In complex networks, the efficiency of information flow is measured in terms of average path length. This measure is defined as the average number of steps along the shortest paths for all possible pairs of network nodes. For example, Yan (2014) uses the measure of average shortest path length (ASPL) to determine the knowledge flow patterns amongst various scientific disciplines. The author argues that ASPL indicates the ease with which a nodes' knowledge can be accessed by other nodes. Using this measure the author concluded that the social-science domains are more self-contained, and it is more difficult for knowledge from other domains to flow into them. Knowledge from science domains (biochemistry, chemistry and physics) flows more easily to other domains. ASPL quantifies the distance between two specific nodes. A larger path length would indicate that the knowledge has traversed multiple "hops" before reaching the invention, which may affect its appropriation. On the other hand, a shorter path length would enable efficient transmission of information from the knowledge element to the invention without loss of information.

Another way to assess information flow is through the examination of network connectivity. Connectivity of a network describes the presence of a path between every node in the network. A commonly assessed feature when discussing the connectivity of a network is the size of the giant component. A giant component is a connected component of the network that contains a significant proportion of the entire nodes in the network. Kim et al. (2014) measure the size of the giant component to assess the connectivity of members in an organization. The aim of this research was to study the knowledge flow amongst individuals and business units and suggest steps that should be taken to prevent knowledge sclerosis. Being part of the giant component ensures that one has access to other members of the giant component and hence can benefit from their knowledge. Thus, larger the size of the giant component, the higher is the potential of knowledge flow from different knowledge elements. Measuring connectivity of the knowledge network should hence inform us of the degree of knowledge spillovers leading to the invention.

One of the ways of incorporating connectivity and path length in assessing the performance of a network is through the measure of robustness. Network robustness, described in statistical mechanics of complex networks, tests the ability of the network to continue functioning despite disruptions. Disruptions in a network occur when its nodes and/or edges are removed progressively such that the network disintegrates, that is, nodes become disconnected from the network. This measure finds application in many fields. In biological networks it helps us gain an insight into the propagation of diseases and immunity developed towards them (Costa et al., 2007; Kiss et al., 2008; Lu et al., 2016). In communication networks, such as the Internet, it helps us understand the behaviour of the system in case of failure of the routers (Zhang & Cantwell, 2013). Transportation networks can be better designed with the knowledge of how disruptions affect them. Social scientists use this measure to explore the firmness of human society when faced with natural or man-made disasters (Biggiero & Angelini, 2015; Lauchs et al., 2012; Liu et al., 2011). It is thus, apparent that this measure has many real-world applications.

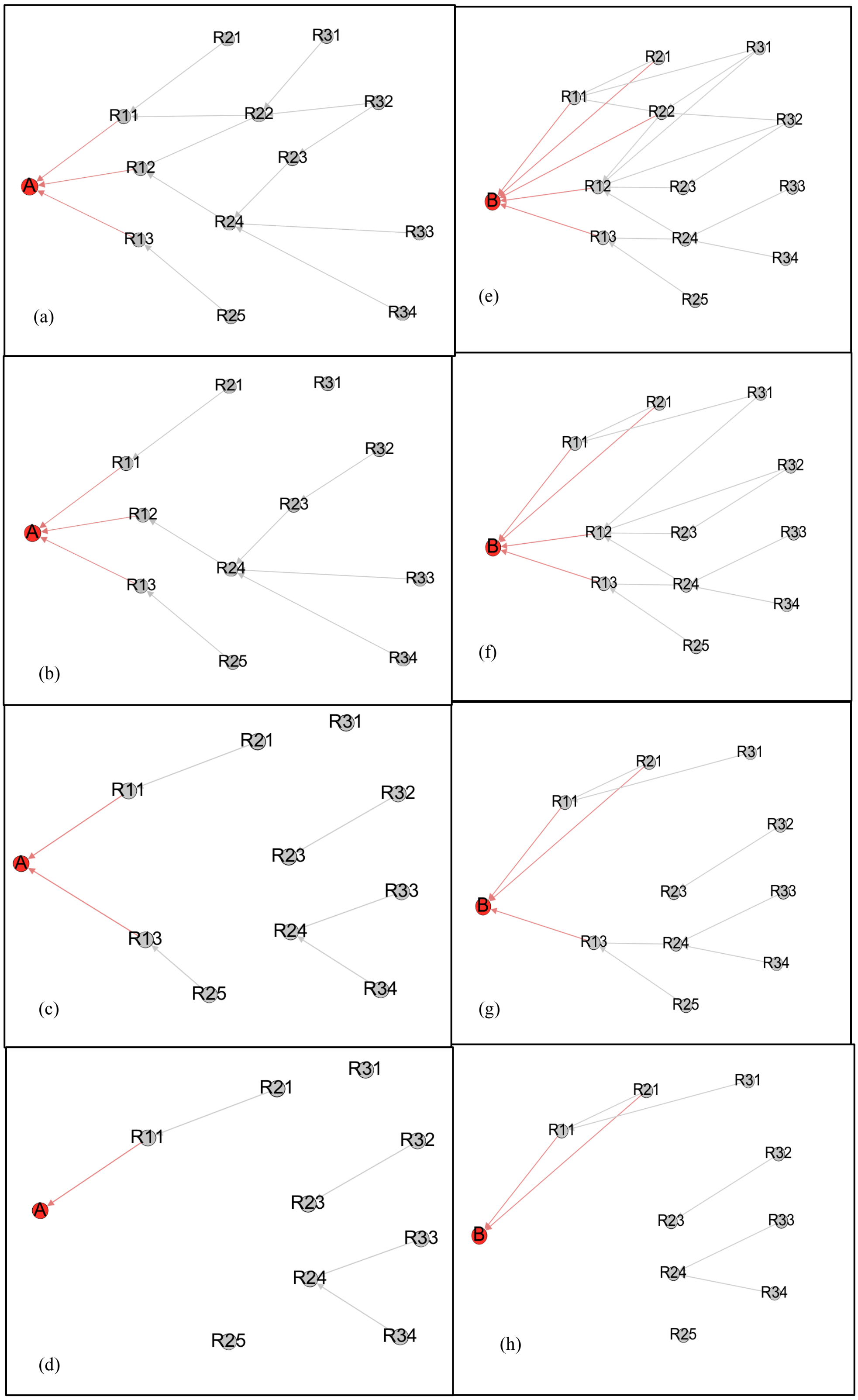
Knowledge spillovers create edges that connect two knowledge elements. A higher level of knowledge spillovers in the technological sector should lead to more edges that link different parts of the network. A higher number of links would therefore, enhance the flow of information within the network, in turn supporting knowledge generation. Such linking would also enhance the robustness of the network. I argue that the robustness of a knowledge network is an indicator of the degree of knowledge appropriation within an invention. The robustness of a network is typically assessed by removing its nodes or edges (randomly or strategically) one at a time and measuring the performance of the network. In a highly robust network, more nodes need to be removed before the network disintegrates, as compared to a weaker network. The disintegration of a network indicates that it cannot perform the function for which it was designed. In the context of this research, the intended function is knowledge spillover from one invention to another. A knowledge network could be considered disintegrated if it is unable to facilitate the required knowledge to flow. The robustness of the knowledge network preceding an invention should therefore, indicate knowledge appropriation within an invention.

Consider the following examples of invention A and invention B (Figure 5-1). The knowledge network of these inventions is represented by their respective patent citation network. The networks are directed acyclic graph with each node representing a patent and edges representing the citation links. The direction of the edges points the direction of knowledge flow. Each of these inventions draws its knowledge from a similar knowledge base. Let the knowledge spillovers in the knowledge network of invention A be fewer as compared to invention B. Now consider the knowledge flow path length in these networks. The path length between nodes $R_{31}$ - A and $R_{32}$ - A is 3 (Figure 5-2a). Knowledge from $R_{31}$ reaches A in 3 steps. In invention B, path length between nodes $R_{31}$ - B and $R_{32}$ - B is 2 (Figure 5-2e). In these knowledge structures, consider the removal of node $R_{22}$. This act also removes the edges connected to it. As a result the path length between $R_{31}$ and A becomes infinite (Figure 5-2b). In other words, no path remains for information to pass from $R_{31}$ to A. The path length between $R_{32}$ and A increases to 4 (due to the existence of alternative path $R_{32}$-$R_{23}$-$R_{24}$-$R_{12}$-A). However, in invention B due to a higher level of knowledge spillovers, alternative paths between $R_{31}$ – B and $R_{32}$ –B exist because of which the path length remains unaffected (Figure 5-2f). In invention A, further removal of nodes gradually increases the path length between node A and the rest of the nodes in the network until the path length between them becomes infinite. At this point, information ceases to flow from the knowledge network to node A due to absence of paths (Figure 5-2d). Hence, the invention will not have the necessary knowledge flowing to it. On the other hand, due to higher number of knowledge spillovers in the knowledge network of invention B, more nodes need to be removed in order for the path lengths to become infinite and to isolate node B from the rest of the nodes in the knowledge network.

A higher level of knowledge spillovers result in enhanced knowledge flow within the technological domain. In such a domain even after the removal of a few knowledge elements (nodes), enough paths (edges) exist for the knowledge to flow from remaining knowledge elements to the invention. On the other hand, in a poorly connected network, the removal of just a few nodes will detach the target patent from the rest of the network, indicating poor knowledge appropriation. Therefore, the robustness of the knowledge network preceding an invention is an indicator of knowledge appropriation within the invention. Therefore, I hypothesize:

*HYPOTHESIS 1B: The knowledge appropriation in the knowledge structure is positively correlated with the technical value of the invention.*

**Figure 5-1: Robustness of Knowledge structure of invention A and invention B**



## 5.4 Summary

Knowledge and its accumulation have been known to be important contributors to growth in various domains. It has been known to boost innovation in organizations and has been used as an indicator of technological maturity of sectors. Thus, knowledge accumulation should be an indicator of the technical value of inventions. Research has revealed that inventions employing highly mature technologies successfully produce products and provide stepping-stones for future inventions thus, demanding a high value. Knowledge accumulation of an invention indicates the methods, procedures and ideas that have come together to create the invention. It therefore represents the research efforts that have taken place to make the invention possible. Technology assessment techniques based on growth curves currently do not consider the research efforts behind an invention. Thus, in order to assess the technical value of individual inventions, the knowledge accumulation behind the invention should also receive attention. The knowledge structure of an invention gives us the opportunity to measure the knowledge accumulation of an invention.

Knowledge flow within the knowledge structure indicates that old concepts or procedures have been appropriated for new knowledge creation. The significance of knowledge spillovers for innovations has triggered research efforts that attempt to understand its various facets. Knowledge spillovers are created by active research in a technological sector. Such spillovers enhance knowledge flow in the sector and provide solutions to the technological problems. From a complex network perspective, knowledge spillovers create edges that link different parts of the network thus, improving the connectivity within the network. Such linking also improves the robustness of the network. In a robust knowledge network enough knowledge paths exist for the knowledge to flow from the network to the invention leading to an efficient knowledge appropriation. Thus, the robustness of the knowledge network preceding an invention should be an indicator of knowledge appropriation within the invention.

# 6 METHODOLOGY

## 6.1 Introduction

In this chapter I detail the methodologies that I have adopted for the analysis. Section 6.2 covers the technique used for collecting data. In section 6.3, I describe the construction of the patent citation network. Section 6.4 describes the technical value of the patents followed by its computation. In sections 6.5 I derive the metric for calculating knowledge accumulation of invention. Section 6.6 describes other technical value indicators mentioned in the literature that have been used in this study. Sections 6.7 and 6.8 detail the metrics and methodology used for measuring the network robustness.

## 6.2 Data Collection

Patent data for this research was collected from Espacenet. This database is ideally suited because the intention of the research was to capture the knowledge background of the inventions at an international level. Patents sometimes refer to other patents that have been granted in a different jurisdiction than their own. In such cases, Espacenet provides access to a consolidated database with over 90 million patent publications from 90 countries. I used patent classification codes for searching patent data. Different countries adopt different classification systems. For example, the German patent classification is given to patents granted in Germany and a few other European countries and United States Patent Classification (USPC) is given to patents granted in US. International Patent Classification (IPC) was created under Strasbourg Agreement 1971 and is administered under World Intellectual Property Organization (WIPO). Over 100 countries use this system in order to classify patents in a systematic manner. In order to minimise the differences in these classifications, the European Patent Office and United States Patent and Trademark Office created a cooperative Patent Classifications (CPC). Adams (2001) notes that the classification scheme reflects the environment in which they are produced, culture of the country in which they are developed, and the intended scope of retrieval. For this reason, one would find differences in how an invention is classified by different patent offices.

Two of the highly used classifications in patent analysis studies are IPC and USPC. IPC provides a platform for uniform patent classification across different jurisdictions. This system of classification has 8 sections, labelled A to H, which are further divided into groups and subgroups. These subdivisions amount to approximately 70,000. This classification system is revised periodically to improve the system and to take account of technical developments. For example, a new class of B82Y was introduced in 2011 for classification of nanotechnology structures. When the classification is revised, patent documents are reclassified according to the amendments. The USPC was started in 1836 and was in use until 2015. It has around 130,000 subdivisions. This classification was revised every two months and the revisions were cumulated and reloaded annually.

Adams (2001) concludes that the USPC system is more responsive to subject matter changes. However, USPC revision concordances are not publicly available, unlike for IPC. Concordances permit the searcher to track back in time to identify the most appropriate class mark for each time period. Adams (2000) argues that lack of revision concordance for USPC makes it an awkward choice when searching across large year ranges.

The aim of this research is to assess the knowledge structure of inventions. The knowledge elements that form the invention could come from any part of the world. Following USPC would restrict the search to a specific geographical region (USA) as this scheme of classification is not adopted by other countries. Similarly, it is observed that not all the patents mention CPC classification on their original document. Thus, adopting either of these classifications would provide an incomplete picture of the knowledge structure. A possible solution would be to look for concordances between the classifications. However, this would complicate the process. It is important to choose a classification that has been adopted by many countries. This ensures that while tracing the knowledge roots, even if the patent refers to a patent that was granted in a different country, there will not be any discrepancy in the subject area. Thus, my research utilises IPC for creating co-classification-based citation network. This study analyses patent data from four sectors: Thin film photovoltaic (TFP), Inductive vibration energy harvesting (IV), Piezoelectric energy harvesting (PZ) and carbon nanotubes (CNT).

The following steps were carried out in shortlisting the target patents:

a) Using a combination of keywords and International Patent Classification (IPC) codes, relevant patents in each sector that were granted in US, were shortlisted. The time frame for search was 1990-1992 for TFP sector, 1989-1991 for PZ sector, 2000-2002 for CNT sector and 1989 onwards for IV sector. Due to relatively scarce patenting activity in the IV sector, I broadened the time frame for samples. In this sector I included the patents that were granted from 1989. The upper limit was set to patents filed in or before 2007. Different time frames were used in the search of the patents due to differences in the technological development in these sectors. For example, the research activities in TFP and PZ have existed relatively longer than the activities in CNT development. Thus the time frames were chosen in such a way that these inventions had had enough time to accumulate citations and at the same time there was an observable period for knowledge structure to form. In TFP, PZ and CNT sectors the narrow window of time frame ensured that the citations of these inventions are comparable and do not need additional standardization. For IV sector, the citations were normalized as explained in section 6.4 of this chapter.
b) To determine the relevant IPCs for each sector I referred to the literature. Patent landscape reports published on WIPO (World Intellectual Property Organization) provided the initial search point for identifying the relevant IPCs for CNT and TFP technologies. This was later cross-checked through studies in this sector that performed patent studies (Liu et al., 2009).

For PZ and IV sector I adopted a different approach because of lack of patent studies in this area. For these two sectors I analysed the patents granted to the companies that operate in this area such as Perpetuum, Ltd., Enocean GMBH, Innowattech, and Mide Technology. I studied their patent portfolio to determine the relevant IPCs and appropriate keywords relevant to the sector. TABLE 7-1 gives a description of the chosen IPCs for each sector.

c) For each sector the appropriate keywords were shortlisted after scanning the relevant literature pertaining to the technologies being studied. For example, for PZ sector the keywords "piezoelectric" and "piezo" were used. For CNT sector "CNT", "nanotubes", "carbon nanotubes" were used. For IV sector, "inductive", "Vibration", "vibration energy", etc. were used. For TFP sector, "thin film", "solar", "photovoltaic" etc. were used. These keywords were used in various combinations along with the keyword "energy harvesting" and the relevant IPC of the sector. The purpose was to perform an exhaustive search for the patents relating to these technologies. For PZ sector IPCs H02N2 and H01L41 were used for the initial search. For the CNT sector, IPCs C01B31 and D01F9 were used. For the sectors IV and TFP, IPC H02K35 and IPC H01L31 were used respectively. The initial search yielded 279 PZ, 101 CNT, 296 IV and 223 TFP publications.

d) The resultant patents were then sifted manually to include only the patents that had the above-mentioned IPCs as the main and preferably the only IPCs. In order to achieve this task, the original documents of the patents were examined. The main IPC of a patent is mentioned in bold on the front page of the document, against "Int. Cl." This ensured that the focal technologies (piezoelectric energy harvesting, carbon nanotubes and inductive vibration energy harvesting) were the main technologies and not the supporting technologies of the described invention. I then manually screened the abstract and description of each patent to ensure that they described inventions pertaining to the field chosen. For example, in the CNT sector, only patents describing the manufacturing of CNT were included. Patents that described devices that used CNT as one of the components were excluded. I also ensured that none of the patents from the list came from the same patent family. Thus, the final list included 53 granted patents from PZ sector, 25 granted patents from CNT sector, 45 granted patents from TFP sector and 29 granted patents from IV sector.

## 6.3 Patent Citation Network

The beauty of citation networks lies in the fact that different aspects of the knowledge can be uncovered based on how these citation links are explored. For example, citation links based on the inventor or assignee (self-citation) reveal the continuity of knowledge flow within an entity (Hall et al., 2005; Jaffe et al., 1993). Tracing citation links based on geographic location sheds light on the effectiveness of knowledge diffusion across geographical boundaries (Bell & Zaheer, 2007; Sorenson et al., 2006). Tracing non-patent citations gives us information on the developmental level of the technology; i.e. is the technology closer to science or is it at application level (Trajtenberg, 1997).

To understand the knowledge background of patents, Ellis et al. (1978) traced the references of a patent. They started with 10 initial patents and noted their references. These references were then examined by field experts to determine their relevance to the field. The irrelevant patents were discarded. The references of this generation were noted, and the process was repeated. The main draw back in this methodology is that one would need a domain expert in order to analyse the relevance of patents to a field. An alternative way would be through the use of classifications.

Patent classification is a system adopted by the patent examiners to code the patent documents according to the technical features of the invention described in the document. One of the main advantages of the classification is that it enables the efficient searching of patents. Patent examiners first study the patent to determine its subject matter. Once the subject matter is determined, every claim is then considered separately for classification code. Larger the number of technological codes, larger is the number of distinct technologies constituting the patent (Strumsky et al., 2012). Co-classification based citation links reveal knowledge flow within or between different technological sectors. Two patent documents receiving the same classification indicate the relatedness in knowledge. Co-classification has been used in the past successfully to analyse various aspects of a patent network. For example, Leydesdorff (2008) showed that co-classification analysis at 4 digit level was much more connected than it was at 3 digit level when analysing the relations among technologies at different levels of aggregation. Breschi et al. (2003) used co-classification in 2003 to show that knowledge relatedness is a key factor in affecting firms' technological diversification. Engelsman and van Raan (1994) used co-classification to map technological developments, its structure and relations between various fields of technology. Studies have also demonstrated the use of this technique for the purpose of tracing prior knowledge (Curran & Leker, 2011).

In order to create the knowledge structure of the inventions, I traced the references of the patent within the focal IPC. This ensured that I included all the knowledge elements pertaining to the core technology of the invention. Thus, a co-classification based citation network was used to represent the knowledge structure of inventions. The following steps were followed in creating the knowledge structures:

a) In each of the shortlisted patent from each sector, the references were identified. In these references, only the patents carrying the core IPC of the field were recorded while the remaining were discarded. For example, for IV sector only the patents containing IPC H02K35 were recorded while the remaining discarded. In TFP sector references containing IPC H01L31 were retained. In PZ sector a reference was retained if it contained at least one of the chosen IPCs; H02N2 or H01L41. Similarly, for CNT sector, a reference was retained if it contained at least one of the IPC; C01B31 or D01F9. This formed the first generation of backward citations.
b) The above-mentioned process was repeated with each one of the references of patents in this level to form the second-generation backward citation network.
c) The process was continued until no new relevant patent was found in the references.

d) The year of application of each patent in the knowledge structure was recorded.
e) Using the above gathered information citation network for each sample was constructed for visualization purpose using the software Gephi 9.0. Patent citation network of patent US7535148 of IV sector is presented in Figure 6-1 as an example. Figure 6-2 shows the node degree distribution of this target patent.

## 6.4 Patent Technical Value (PV)

Before proceeding further, it is important that I first define patent value for the purpose of this research. The value of a patent is a combination of its technical and commercial value. The commercial value relates to the perceived value of the invention in the market. To a large extent this value is affected by external factors such as the competitive landscape, socio-economic conditions or even the ability of the company to market its products. The technical value on the other hand, relates to the importance that the technology described in the invention holds. An invention with high technical value may have a high commercial value as well (provided the technology has commercial applications), however a low technical value will not yield any commercial value. Technical value of inventions may be linked to their technological maturity. Research has shown that mature technologies have a higher probability of being implemented into products (Beierlein et al., 2015; McNamee & Ledley, 2013; McNamee & Ledley, 2012). Such technologies also form the foundation to successive inventions, and hence considered high value. This thesis focuses on assessing the technical value of inventions and considers it as an indicator of technological maturity of the invention.

Patent variables such as claims, citations, references, family size etc. have been shown to correlate with technological and commercial value of a patent. For example, the number of claims (Baron & Delcamp, 2011; Lerner, 1994), renewal data (Bessen, 2008a) and patent family (Harhoff et al., 2003; Sternitzke, 2009) have been shown to be the indicators of the commercial value while citations (Ellis et al., 1978; Narin, 1987; Trajtenberg, 1990) have been widely accepted as an indicator of technical value. However, certain discrepancies exist between the results from various studies. For example, Lin et al. (2007) found a positive correlation between the number of prior art a patent refers to and its value. However, Lanjouw and Schankerman (1997) conclude that the influence of references is insignificant. Volodin (2012) shows that longer examination time decreases the private value of innovations while the results from Lin et al. (2007) research on biotechnology patents found a positive relationship between examination time and citations received. It is often observed that some highly cited patents do not complete their term (lapse due to non-payment of renewal fee), while some weakly cited patents enjoy protection in many countries. Discrepancies in the results could be due to the differences in the research methodology, analysis and sectors. The patenting trends vary from sector to sector, which may influence how the patent variables correlate with the patent value. Thus, results observed in one sector may not be applicable to other sectors. van Zeebroeck (2011) notes that, despite their common correlation with patent value, the patent indicators are in fact weakly correlated with each other. Thus, if one were to rank a group of patents based on these individual indicators, the different indicators would produce different rankings. This makes it difficult to separate the high value patents from the low value ones. To overcome these differences, researchers have suggested combining patent indicators to obtain a composite patent value (Hall et al., 2007; Lanjouw & Schankerman, 2004; Thoma, 2014; van Zeebroeck, 2011). These researchers claim that since all the patent indicators correlate with patent value with some variance, combining the indicators would help localize that value. Hence depending on which indicators are combined, one can extract either the technical value or the commercial value of the patent.

In this research, to extract the technical value of the patent, I create a composite patent value by combining forward citations, references, patent family size and patent survival term. These indicators have been explained in depth in section 2.3.1 of CHAPTER 2. Thus, I only give a brief description here.

a) ***Citations:*** A patent receiving citations from subsequent patents is an indication of its technical value. The difficulty with using citation counts is that they take time to accrue and patents continue to receive citations even after their term. This makes comparison between patents filed in different years difficult. One of the solutions adopted in the literature to overcome this difficulty is to limit the citations to the first few years of the patent life (Lanjouw & Schankerman, 2004; van Zeebroeck, 2011). The dataset in this research shows two different filing behaviours. Patents from TFP, PZ and CNT sectors were filed within three years of each other. Hence, for calculating the composite technical value of patents from these sectors, all the citations received by the patents till date were considered. On the other hand, patents from IV sector have a longer time period between their filing dates. Thus, for these samples I only consider the citations received in the first five years after their filing for calculating the composite technical value.

b) ***Family and survival term (Scope-Year index)****:* Size of the patent family, represented by the number of countries in which protection is sought for an invention, and its survival term have been shown to be positively correlated to the patent value (Harhoff et al., 2003). This implies that the invention is technically strong and has commercial importance in a larger geography. Hence, the family size and survival term of a patent indicates technical value of invention. I utilise the scope-year index as proposed by van Pottelsberghe de la Potterie and van Zeebroeck (2008) to capture the geographical scope and term survival of the patent. This indicator is expressed as:

$$SY_{\mathrm{A}} = \frac{\sum_{y=1}^{Y}\sum_{r=1}^{R} G_i(r,y)}{R*Y} \tag{6-1}$$

where $SY_A$ stands for the Scope-Year index of a given patent *A* over *R* countries and *Y* years of maintenance. *Gi(r,y)* is a variable that takes the value 1 if the granted patent *i* in the patent family of *A* was active in country *r* in year ***y*** from its filing date, and 0 otherwise. The index is normalised to its maximum value representing *Y* years of maintenance in *R* countries. I set *Y* to 10 years, which takes into account 2 renewal periods of the patent. I referred to the USPTO (US Patent and Trademark Office) Patent Application Information Retrieval (PAIR) website (https://portal.uspto.gov/pair/PublicPair) and EPO (European Patent Office) Global Dossiers for information on patent legal status.

c) ***References:*** References, also known as backward citations, represent the knowledge foundation of the patent. Studies have shown that patents referring to more prior art tend to be more valuable (Harhoff et al., 2003; Lin et al., 2007). Hence, a longer and more diverse reference base indicates a larger technical knowledge base, which should be indicative of the technical value of the patent. I do not take into account non-patent references such as journal articles.

### 6.4.1 Calculation of PV

In patent studies, such as those by Lanjouw and Schankerman (2004), van Zeebroeck (2011), Thoma (2014) and Hall et al. (2007), scholars have used factor analysis to create a composite patent value. However, due to the limitations of sample size, I use a more generic mathematical approach described by Song et al. (2013). In this approach, the sum of the *z* scores for each of the above-mentioned patent variable is transformed to a *T* score to create the composite technical value of the patent. A *z* score is a numerical measurement of a value's relationship with the mean in a group of values. The *z* scores have a mean of 0 and a standard deviation of 1 and range from positive to negative numbers. A *z* score of 0 implies that the score is identical to the mean value. This normalises the distribution of the values. Converting these values to *T* score then returns the results from between 0 to 100.The patent value, PV, is thus, calculated as:

$$PV = \overline{X'} + \frac{\sum_{v=1}^{V} z_i}{V}(SD') \qquad (6\text{-}2)$$

where $V$ denotes the number of patent variables, $z_i$ denotes the *z* scores of these patent variables, $\overline{X'}$ is the new desired mean and $SD'$ is the desired standard deviation. I set $\overline{X'}$ to 50 and $SD'$to 10 as suggested by Song et al. (2013). For each patent in the sample set, I calculated the patent value as per the method described above.

I used the following steps in calculating the technical value of the patents in my dataset:

a) I recorded the following information about each patent in the sample set: number of references (excluding non-patent references), number of forward citations (for IV sector I only record the citations received in the first 5 years of the patent life), family size, legal status of each family member and date of filing.
b) I first determined the scope-year index of each patent using Eq. (6-1).
c) I then converted the number of references, number of citations and scope-year index into their respective z scores. *z* score is calculated by subtracting the observation with the mean of all observations and dividing the result by the standard deviation of all observations.
d) I then used Eq. (6-2) to calculate PV.

## 6.5 Knowledge Accumulation (KA)

In this section I derive the equation to measure the knowledge accumulation in inventions. The knowledge accumulation of an invention may be revealed through its knowledge structure. The rationale behind the knowledge structure has been discussed in CHAPTER 3. A patent citation network, as discussed in CHAPTER 4, is one of the ways to visualise this knowledge structure. A patent document lists references that indicate the prior art on which the invention is based. References of references can be traced back in time to create a multi-generation patent citation network, which is indicative of the knowledge structure of the invention. Based on the patent citation network, I derive the metric for knowledge accumulation in this section.

Assuming patent *A* represents invention **A**, then the knowledge accumulation (KA) for patent *A* can be given as:

$$KA_A = \frac{n_A}{\sum_{m=1}^{M} N_m} \qquad (6\text{-}3)$$

where $n_A$ is the total number of patents in the knowledge structure of the target patent, i.e., the volume of knowledge that has been used in creating this patent. $N_m$ represents the number of patents existing in patent class $m$ up to the year of filing ($T_x$) of the patent *A* and *M* represents the number of patent classes that together describe the technology of the sector. The equation aggregates the efforts that have taken place in the sector before the target patent. A larger $n_A$ indicates that the target patent sources a larger body of knowledge. A larger $N_m$ indicates more knowledge existing in the sector and hence more possible solutions from which to choose.

However, the knowledge for the target patent should be scaffolded by mature technology. Each piece of knowledge associated with the patent is itself scaffolded by other technology, and the maturity of this overall knowledge structure is relevant in calculating knowledge accumulation. I therefore, introduce a time factor to take into account the age of the knowledge that precedes the target patent. The time factor permits the metric of knowledge accumulation to account for structural maturity rather than a simple chronological measure of (knowledge) age for the target patent.

Knowledge used in this patent can hence be represented by:

$$n_A = \sum_{i=0}^{x} n_i(T_x - T_i) \qquad (6\text{-}4)$$

where $n_i$ is the number of patents filed in year $T_i$ in the knowledge structure of patent *A*. The subscript *i* takes the values *0, 1, 2, 3, …, x-2, x-1, x*, where $T_0$ indicates the year of application of the earliest patent in the knowledge structure and $T_x$ indicates the year of application of the target patent *A*. I also take into consideration that while both long-term knowledge and recent knowledge are needed in creating inventions, recent knowledge is more influential (Nerkar, 2003). To take into account the influence of recent knowledge, I introduce the weighting factor $\alpha_i$:

$$\alpha_i = 1 - \frac{T_x - T_i}{T_x - T_0 + 1} \qquad (6\text{-}5)$$

Making the appropriate algebraic substitutions, the knowledge accumulation of patent *A* can be represented by:

$$KA = \frac{1}{\sum_{m=1}^{M} N_m} \sum_{i=0}^{x} \alpha_i n_i \, (T_x - T_i) \qquad (6\text{-}6)$$

Equation (6-6) represents the knowledge accumulation of inventions.

## 6.6 Existing Patent Valuation Metrics

I compared the metric of KA with other technical value indicators mentioned in the literature. I calculated the following metrics for all the target patents in the dataset:

a) Hu et al. (2012) used indicators based on a patent citation network, also termed an "ego patent citation network" in their work. They define the *Technical Interest Index (TII)* of a patent as an indicator of the innovative density of the technological knowledge flow. It is measured as the squared root of the total number of citations of its references.

$$TII = \sqrt{CIT} \qquad (6\text{-}7)$$

where *CIT* denotes the total number of citations received by the references of patent ***A***. The authors argue that a patent's technical value reflects its technological knowledge base, knowledge flow, and technological complexity.

b) The technical value of an invention has also been defined through its "basicness" or its closeness to science. Trajtenberg (1997) suggests that "basicness" can be measured through the following equation:

$$\mathrm{IMPORTB} = \mathrm{NCITED} + \lambda \sum_{j=1}^{ncited} \mathrm{NCITING}_{A-1,j} \qquad (6\text{-}8)$$

where *NCITED* is the number of patents cited (references) by the target patent ***A***, λ is a discount factor (0< λ <1) meant to down weight the second-generation patents*, A-1* indicates the cited patents, and *NCITING* is the number of patents citing the originating patent. In other words, *NCITING* is the citations received by the references of the target patent. *IMPORTB* reflects the extent to which a given patent stands on a wide base of previous inventions that are themselves important. Trajtenberg argues that more basic patents would have fewer important predecessors and therefore, lower values of *IMPORTB*. Academic patents are considered more basic in nature. Such patents, while introducing new or radical knowledge, do not result in commercial products immediately (Czarnitzki et al., 2009) as the technology is not mature enough yet. This indicates a nascent level of research/knowledge underlying the invention.

c) Narin (1993) uses *Technology cycle time* (TCT) to determine the length of time it takes a firm to use a new technology. It is measured as median age of the patents cited by a given patent. A shorter TCT indicates a higher patenting activity in the area implying higher technological strength. Bierly and Chakrabarti (1996) showed that a high knowledge base level in a firm will lead to faster technology cycle time by allowing members of the firm to better understand and interpret external advances in the field and allowing the firm to combine new technologies effectively with other complementary technologies.

d) Trajtenberg (1997) describes the value of a patent through its *Originality and Generality.* Originality is a measure of the technological roots of a patent. A large "Originality" value indicates a broader technological roots of the underlying research (Trajtenberg, 1997). The idea behind this measure is that highly original research is an outcome of coming together of divergent ideas. This relationship is expressed as:

$$ORIGINAL = 1 - \sum_{m=1}^{M} \left(\frac{NCITED_m}{NCITED}\right)^2 \tag{6-9}$$

where ***m*** is the index of patent classes, and ***M*** the number of different classes to which the cited patents belong. *NCITED* is the total citations made by patent ***A*** and $NCITED_m$ is the citations made in each patent class ***m***. Originality is a measure of the diversity of the knowledge roots of a patent and not necessarily of the quantity of that knowledge.

e) The Generality of a patent is the extent to which the follow up technical advances are spread across different technological fields, rather than being concentrated in just a few of them. This has been represented as:

$$GENERAL = 1 - \sum_{m=1}^{M} \left(\frac{NCITING_m}{NCITING}\right)^2 \tag{6-10}$$

where ***m*** is the index of patent classes, and ***M*** the number of different classes to which the citing patents belong. *NCITING* is the total citations received by patent ***A*** and $NCITING_m$ is the citations received in each patent class ***m*** associated with patent ***A***. The value of *GENERAL* ranges from 0 to 1, with 1 indicating less concentration and 0 indicating high concentration within patent classes. Trajtenberg argues that a highly general patent provides a base for numerous subsequent technological changes. Such patents may receive high social returns. Fischer and Leidinger (2014) observed that a higher generality increased the probability of a patent to be traded, and Mathew et al. (2012) observed that the generality of a patent is positively correlated to its price. While the generality of a patent indicates that more subsequent inventions from different technology classes are based on it, it is not necessarily an indicator of the knowledge base of the patent itself. However, a high *GENERAL* has been observed in highly cited patents. This indicates that the technical maturity of an invention contributes to its Generality at some level.

## 6.7 STRUCTURAL ROBUSTNESS as a measure of Knowledge Appropriation

Testing the robustness of a system involves evaluating its integrity after the removal of a node. In real-world situations, the removal of a node could simply imply that it is non-functioning. For example, in testing the robustness of biological network to the propagation of diseases, node-removal indicates that that specific entity is immune to the disease and thus, will not contribute to the transmission of the disease. In a knowledge network node-removal implies non-availability of information from that entity. The removal of a single node may not damage the integrity of the network. However, persistent removal of nodes eventually breaks the network into smaller components. Thus, scientists are mostly interested in the question; how many nodes need to be removed from the network before it completely disintegrates? A network would be considered disintegrated if the remaining connections (edges) or the size of the network is insufficient for it to perform the function it originally was designed to do.

Removal of the nodes could be either targeted or random. For a real-world network, random node-removal indicates accidental failure while strategic node removal indicates deliberate attack on the network. Thus, the node-removal strategy is chosen based on the network and the intended analysis. Either way, the purpose of robustness analysis is to choose a node-removal technique that causes most damage to the system. This enables us to study the behaviour of the system in face of extreme situations. Scale-free networks are known to be more robust to random attacks (Bonabeau & Barabási, 2003) while random networks behave similarly to both random and strategic attacks (Albert et al., 2000). In scale-free networks, the distribution of node degree follows a power law implying that most nodes have few edges while a few nodes have the most edges. On the other hand, in random graphs (also known as Erdös-Renyi network) the majority of nodes have a degree that is close to the average degree of the network. Some of the scale-free networks include the Internet (Albert et al., 2000), social networks, and some biological networks. Studies have found patent citation networks tend to be scale-free (Brantle & Fallah, 2007; Choe et al., 2013).

When deliberately attacking the nodes, one could choose from multiple approaches based on the purpose of the analysis. For example, node degree in a social network indicates the importance of a person within a group. When it comes to studying spreading of epidemics, high degree nodes indicate people who are in contact with many other people and are thus vehicles for the propagation of the disease. Thus, removing nodes based on their degree in such cases helps understand the best way to stop the spread of the disease. Betweenness centrality is a measure of how often a node is located on the shortest path between other nodes in the network. Similarly, closeness centrality, eigenvector centrality and other centrality measures indicate the importance of a node in a network. A node with high betweenness centrality has the capacity to facilitate or limit interaction between the nodes in the link. Thus, it acts as a control bridge for the information flow of the network. From a study on RFID patents, Hung and Wang (2010) concluded that patents with high betweenness centrality in the network play an important role in the transfer of technology knowledge. Therefore, removing nodes based on their betweenness centrality in a knowledge network would help us understand a systems' behaviour to changes in knowledge flow.

The aim behind measuring the robustness of the knowledge structures is to understand knowledge appropriation within the inventions. The robustness of a network indicates its performance when subjected to disruptions. The purpose of a knowledge structure, in the context of this research, is to facilitate the required knowledge flow from the network to the invention. The performance of the knowledge structure may be measured in terms of its knowledge flow pathways and the connectivity. Thus, based on the knowledge flow pathways (path length) and connectivity, I selected the following techniques to assess the robustness of the knowledge structure:

a) ***Measures based on pathways:*** Network diameter and average shortest path length are commonly measured to understand the pathways within the network. From this category, I used the measure of average shortest path length (ASPL) as an indicator of network robustness. ASPL is the average of the shortest distance between every pair of nodes. Ng and Efstathiou (2006) note that ASPL shows two different trends depending on whether the network is connected or fragmented. In a connected network, a smaller ASPL indicates closer distance between nodes while, in a fragmented network, a higher ASPL indicates stronger connection in the network.

b) ***Measures based on connectivity:*** These techniques measure the changes in the connectivity of the network on removal of nodes. Node connectivity (Dekker & Colbert, 2004), algebraic connectivity (Jamakovic & Uhlig, 2007) and natural connectivity (Wu et al., 2011) fall under this category. I measured connectivity in two different ways:

i. ***Disintegration of giant component:*** Node connectivity (NC) measures the minimum number of nodes that must be removed from a network in order to disconnect the giant component (Dekker & Colbert, 2004). A higher value indicates a more robust network. I slightly modified this measure to better suit my purpose. Since the aim of my research is to observe the point at which the knowledge from the network ceases to flow to the target patent, I focused on the detachment of target patent from the network instead of observing the disintegration of the giant component. Thus, in my research, NC measures the fraction of nodes that need to be removed from the network for the target patent to be detached from the network.

ii. ***Complete disintegration of the network:*** In real networks a part of the network may still maintain its integrity despite significant damage. Thus, scholars argue that the robustness measure should take into account the complete disintegration of the network and not just the phase transition of the giant component. Robustness Coefficient (Piraveenan et al., 2013) and R (Schneider et al., 2011) are two examples of metrics that take into consideration the complete disintegration of the network. From this group of metrics, I chose robustness coefficient, RC, as described by Piraveenan et al. (2013). In this technique RC is defined as a ratio of the areas beneath two network disintegration profiles:

$$RC = \frac{A1}{A2}$$

where A1 is the area beneath the profile of the target network and A2 is the area beneath the profile of an ideal network with the same number of nodes. The disintegration profile for a network is a curve generated by plotting the size of the largest connected component against the number of nodes removed. The authors argue that for an ideally robust network the size of the largest component will decrease linearly, while the more non-robust the network is, the quicker it will disintegrate. The change in the size of the largest component will reflect this collapse. Therefore,

$$RC = \frac{200\sum_{k=0}^{N} S_k - 100 S_0}{N^2} \qquad (6\text{-}11)$$

In the context of this study, the target patent cluster is considered the giant component. The target patent represents the invention being studied and the target patent cluster is the cluster to which this patent belongs. It is most reasonable to study the disintegration of this cluster, that is, its disconnection from the rest of the patent network, since this would mean that the target cluster is isolated from the knowledge generated from the other patents.

### 6.7.1 Node Removal Strategy:

Studies have found patent citation networks tend to be scale-free (Brantle & Fallah, 2007; Choe et al., 2013). In scale-free networks the distribution of node degree follows a power law implying that most nodes have few edges while few nodes have most edges. Scale-free networks are more robust to random attacks but are vulnerable to targeted attacks (Bonabeau & Barabási, 2003). Therefore, it was important to first determine the network characteristics in order to choose the appropriate node-removal strategy. I examined the node degree distribution of the sample sets to determine whether they are scale-free. Using Mathematica 11.2, I determined the power-law exponent for the node degree distribution of all the samples. I also calculated the Gini coefficient to determine whether the node degree distribution is homogenous. The Gini coefficient was calculated based on the Lorenz curve.

I also determined whether the patent citation networks of the sample set are small-world. Nie et al. (2016) concluded that to test the robustness of small-world networks, node removal strategy based on betweenness centrality is most damaging. Betweenness centrality is a measure of how often a node is located on the shortest path between other nodes in the network. A node with high betweenness centrality has the capacity to facilitate or limit interaction between the nodes in the link. Thus, it acts as a control bridge for the information flow of the network. From a study on RFID (radio frequency identification) patents, Hung and Wang (2010) concluded that patents with high betweenness centrality in the network play an important role in the transfer of technology knowledge.

I followed the technique adopted by Bialonski et al. (2010) to determine the small-world properties of the networks. I randomly chose 10% samples from each sector in order to characterize the network. The following steps were carried out as per this technique:

a) I calculated the average shortest path length (L) and the clustering coefficient (CC) of the sample network.
b) I calculated the average shortest path length and the clustering coefficient of about 10 random null-networks per sample. The average of these ($L_r$, $CC_r$) values were noted.
c) I calculated $\lambda=L/L_r$ and $\gamma=CC/CC_r$. Values of $\lambda\approx 1$ and $\gamma>1$ are indicative of a small-world network.

Having confirmed the network characteristics, I then tested the robustness of some of the networks through both random node-removal and targeted node-removal. This was done to determine the most damaging node-removal strategy. Based on the results, I then proceeded to determine the robustness of the target patent knowledge structures. Using the software tools Gephi 0.9.2 and Mathematica 11.2, I adopted the following steps in evaluating network robustness:

a) I computed the betweenness centrality of each node in the patent citation network.
b) I removed the node with highest value of betweenness centrality and computed the following after node removal:

i. Size of the giant component
ii. Attachment of focal patent to giant component
iii. Average shortest path length of the network

c) I calculated the network robustness metrics: NC, RC and ASPL.

**TABLE 6-1: Description of the IPC codes chosen for each sector**

| Sector | IPC | Description |
|---|---|---|
| TFP | H01L31 | Semiconductor devices sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength, or corpuscular radiation and specially adapted either for the conversion of the energy of such radiation into electrical energy. |
| IV | H02K35 | Generators with reciprocating, oscillating or vibrating coil system, magnet, armature or other part of the magnetic circuit |
| PZ | H02N2 | Electric machines in general using piezoelectric effect, electrostriction or magnetostriction |
| PZ | H01L41 | Piezoelectric devices in general; Electrostrictive devices in general; Magnetostrictive devices in general; Processes or apparatus specially adapted for the manufacture or treatment thereof or of parts thereof; Details thereof |
| CNT | C01B31 | Carbon; Compounds thereof |
| CNT | D01F9 | Man-made filaments or the like of other substances; Manufacture thereof; Apparatus specially adapted for the manufacture of carbon filaments |

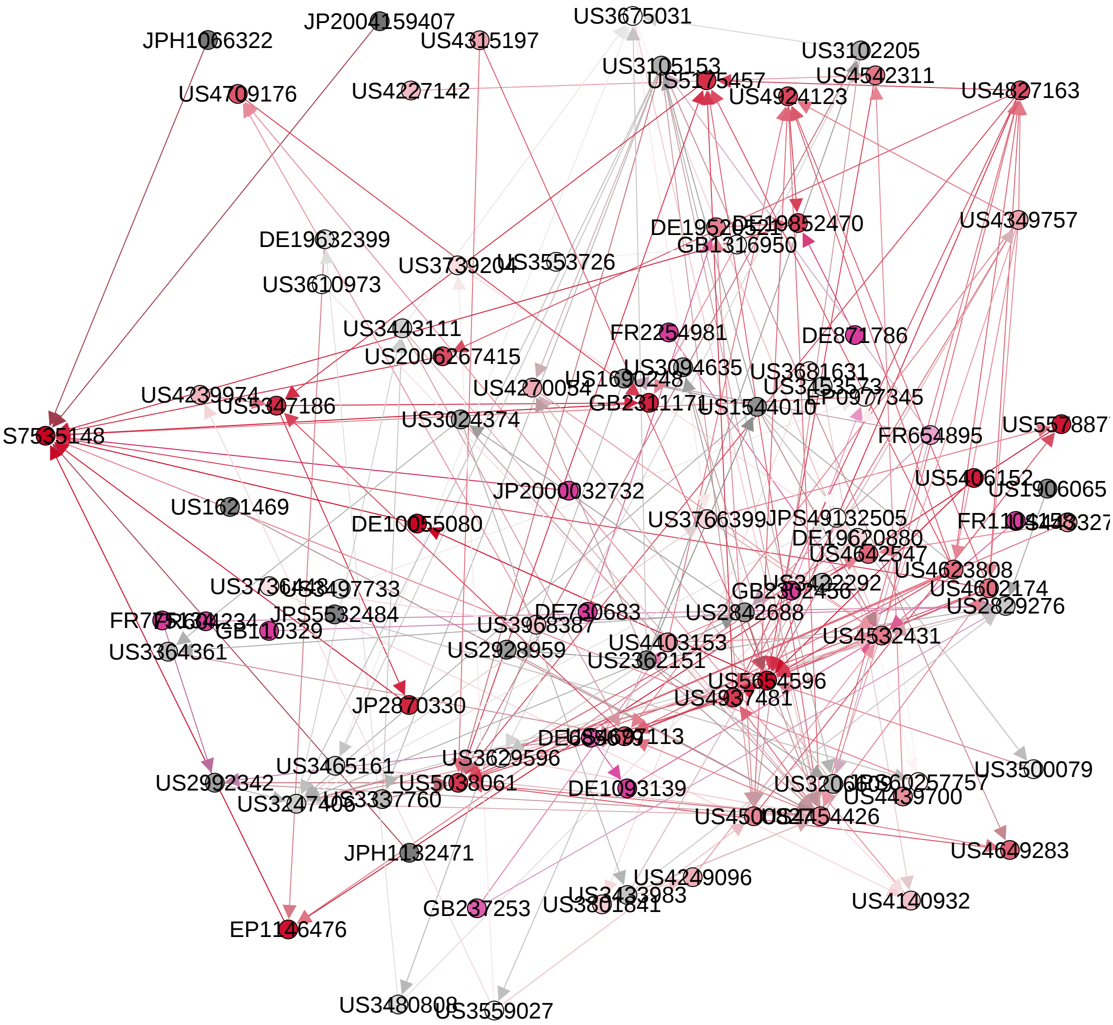



**Figure 6-1: Patent Citation Network of US 7535148**

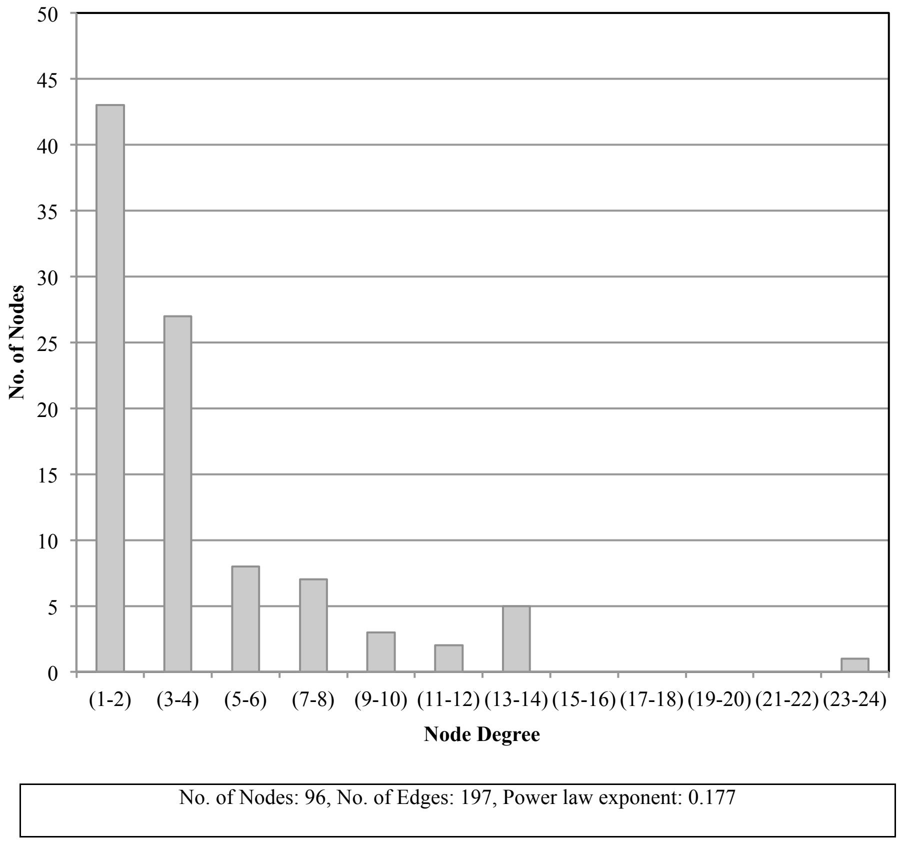



**Figure 6-2: Node degree distribution of US7535148**

# 7 DATA DESCRIPTION

## 7.1 Introduction

The data for this study comes from four different technology domains that find application in energy harvesting: thin-film photovoltaic, inductive vibration energy harvesting, piezoelectric energy harvesting, and carbon nanotubes. Energy harvesting is the process by which energy is derived from external sources (e.g. solar power, thermal energy, wind energy, salinity gradients and kinetic energy), captured, and stored for eventual distribution. The ever-growing demand for energy has been pushing technological advancements in this sector for the past few decades. With embedded and remote systems becoming more attractive, the need to supply uninterrupted power to them has now become an engineering challenge. Batteries suffer from a limited life span and hence need to be replaced regularly. This has resulted in a need for advanced energy harvesting devices. According to market studies, the global demand for energy harvesters is expected to reach $3.3 billion by 2020 ("CompaniesandMarkets.com: Energy harvesting market revenue forecast to be worth US$3.3Bn by 2020: Global Markets, Technologies and Devices for Energy Harvesting," 2015; Research, 2015)

The selection of this dataset for analysis has important economic, environmental, and experimental implications. The inventions in these sectors may be seen as eco-innovations since they not only boost the economic growth, but also lead to sustainable low-carbon systems. Eco-innovations may be the key to reducing greenhouse gas emissions, improving energy security and promoting a green economy. Research by Albino et al. (2014) shows that increased awareness towards environment-oriented lifestyles, favourable government policies and private sector initiatives has stimulated a growth in eco-innovations in many countries. Such eco-innovations tend to be intrinsically interdisciplinary and based upon both recent technological breakthroughs and long-term durable knowledge. Interdisciplinary research can be defined as integration of information, data, techniques, tools, perspectives, concepts and/or theories from two or more disciplines or bodies of specialised knowledge. Such mixing of ideas is known to be a great way to stimulate generation of new approaches to problem solving. For example, photovoltaic systems and wind power require suitable storage such as a battery bank; thus, advances in those systems require a simultaneous interdisciplinary advance in battery technology. Research in wind energy, batteries, and photovoltaic systems has been ongoing for quite some time and include more recent breakthroughs in structure (wind power) and materials (batteries and photovoltaic). Installed systems have taken slightly different technology choices such as the choice of blade design and electricity storage chemistry. Therefore, the knowledge structures of eco-innovations will be useful to investigate as they will be inter-disciplinary, have a long-term history, and have slightly different knowledge structures due to the technology choices of installed systems.

In the following sections, I give an in-depth view of each of the sectors. I start with a general description of the technology followed by the patent landscape of the sector. Patent landscapes give us an understanding of the research activities, competitors, commercial interest and other such information of the sector. I finally give a detailed description of the dataset of each sector.

## 7.2 Thin-Film Photovoltaics

TFP are second-generation solar cells. They are made by depositing a thin layer of photovoltaic material on a substrate, such as metal, glass or even plastic. The commonly used photovoltaic materials are cadmium telluride (CdTe), amorphous silicon, copper indium gallium diselenide (CIGS) and gallium arsenide (GaAs). Techniques such as plasma vapour deposition, chemical vapour deposition and electro chemical deposition are used for depositing the photovoltaic material on the substrate. The earliest products that used TFP were calculators and watches. These solar cells are less efficient (in terms of conversion of solar energy to electrical energy) than crystalline solar cells. Nevertheless, their demand increased in early 2000's due to their low weight and flexibility. According to Jäger-Waldau (2012), over 200 companies were involved in thin film solar activities, ranging from basic R&D activities to major manufacturing activities, in 2011. Within the photovoltaic industry, TFP accounted for 17% of the market share in 2009. However, according to Lee and Ebong (2017), the market share of TFP has been progressively decreasing due to falling prices of crystalline silicon solar cells. Within the TFP industry, CdTe possess the largest market share followed by CIGS (Lee & Ebong, 2017). Chopra et al. (2004) observe that progress on the application of TFP's on megawatt scale has been slow due to problems of reliability with the manufacturing process and the ultimate cost of the device.

Much work has been done to understand and measure interdisciplinarity (Huutoniemi et al., 2010; Kodama et al., 2013; Tijssen, 1992). Kodama et al. (2013) adopted the *Herfindahl–Hirschman* Index (HHI) of control as a measure of interdisciplinarity in their study. Using this measure, I computed the HHI for the four technological areas being investigated. Out of the four sectors the TFP sector is the least interdisciplinary *(HHI=0.581).*

### 7.2.1 Sector Patent landscape

Patents from TFP sector are classified by IPC H01L31. This class of IPC is used to describe inventions in semiconductor devices that are sensitive to infrared radiation, light and electromagnetic radiation. The patent landscape of IPC H01L31 show over 30,000 patent documents published till date. This sector displayed a meagre growth rate of 2% until 2000. Between 2001 to 2012, the patenting activity increased, revealing a 15% year on year growth. Thereafter a decline in the activity is observed. The patenting activity of this sector is given in Figure 7-1.

Japanese patents dominate this sector accounting for over 31% of the total patent publications (Figure 7-2). The first Japanese patent was published in 1960. The patenting in this country grew rapidly in the next 2 decades and accumulated over 7000 publications. There has been an average of over 300% growth per decade in the Japanese patents. This indicates the presence of a strong market for photovoltaics in Japan. US occupies the second place with 22% of all the patents. An average of 155% growth per decade can be seen in patents granted in US in this sector. However, according to a report published on WIPO (FRINNOV, 2009), an analysis of the proportion of patents granted as a function of the number of filings made shows that more patents have been granted in the United States than in Japan. A market report by M2 Communications (Presswire, 2018) states that the thin film photovoltaic market is expected to be dominated by North America and Europe owing to early adoption of technological advancements and Asia Pacific is expected to witness significant growth due to increasing adoption of semiconductors in the electronics industry.

**Figure 7-1: Patenting activity of IPC H01L31**

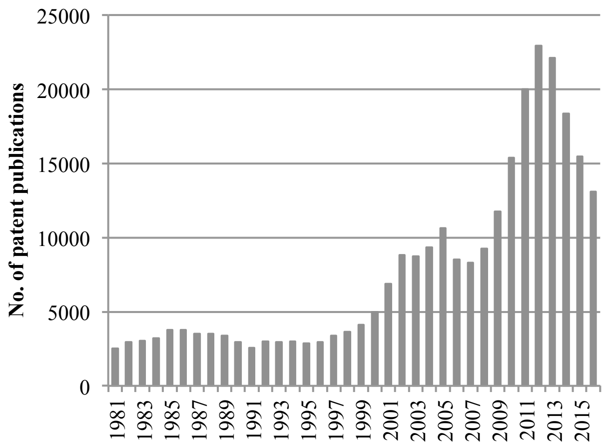
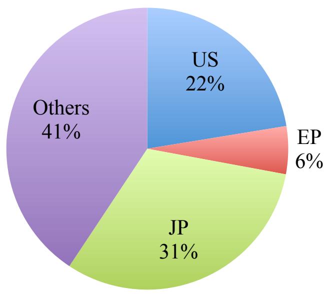


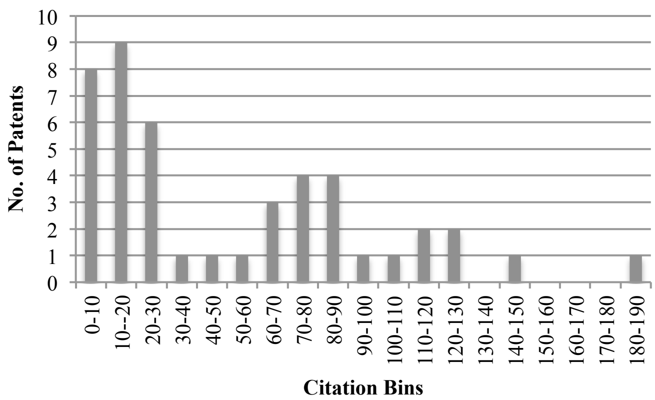

**Figure 7-2: International distribution of patents in IPC H01L31**




### 7.2.2 Data Description

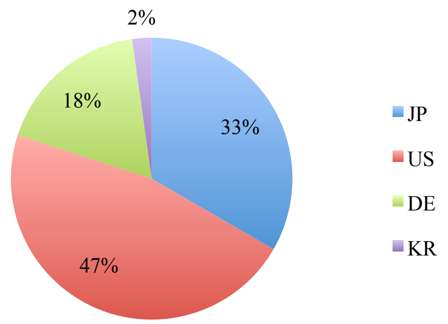
I selected 45 patents from this sector for the analysis. The samples were shortlisted as per the procedure mentioned in CHAPTER 6. These patents were processed in 1.6 years, on an average. 72% of the patents have an inventor team size greater than 2. Out of the four sectors being studied, the patents from this sector display the most number of claims. Each patent protects an average of 17 claims *(SD = 17)*. The samples from this sector display an average of 52 *(SD=45.12)* citations and 9 *(SD = 8.66)* references. The citation distribution (Figure 7-3) of the samples in this sector shows that 80% of the samples have received less than 90 citations.

**Figure 7-3: Citation Distribution of TFP Samples**




These 45 samples are owned by 27 different assignees. Mitsubishi Electric Corporation owns 13% of the patents in this sample set. The assignees in this sample set originate from four countries: US, Japan, Korea and Germany (Figure 7-4). Nearly half the patents belong to US-based organizations and 87% of these US organizations are corporates. The second largest share of the patents is owned by Japanese organizations. Only 3 patents (7% of the samples) are owned by research organizations, out of which one patent is a result of a joint venture between a research body and a corporate organization. Details of the assignees are given in TABLE 7-3. I further provide the financial details of these assignees where possible. These details have been taken from the corporate websites, annual reports, financial websites such as Bloomberg.com and general Internet search. Where the company had been bought over or merged with another corporation, the current financial details have been omitted. The financial details of private organizations were also unavailable. Information regarding six of the assignees could not be located. It is possible that these are small organizations and hence are not yet well known. It is interesting to know that at least four of the assignee organizations; Astropower Incorporated, Solarex Corporation, United Solar Systems Corporation and Siemens Solar Industries LP, have either declared bankruptcy or have been acquired by other organizations. Higher mounting losses and lower product efficiency are some of the reasons mentioned in regards to the closing down of the organizations (Josephine, 2012; World, 2004).

**Figure 7-4: International distribution of the Assignees**




## 7.3 Inductive Vibration Energy Harvesting

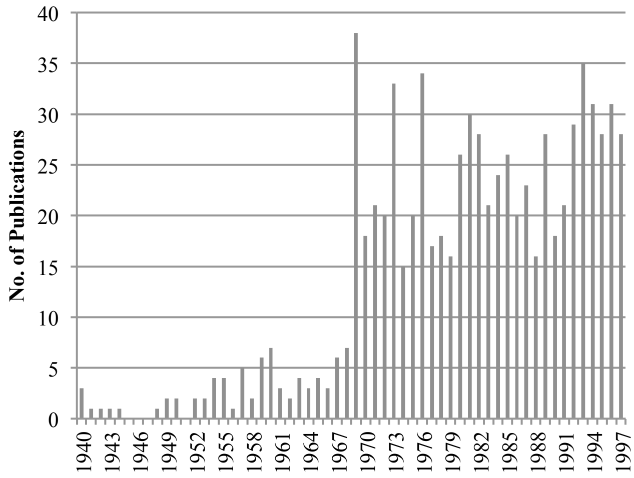
IV energy harvesting involves the use of kinetic energy released by vibrations in the environment to harness energy. These devices contain a magnetic component inside a coil, the relative movement of which produces electricity. Ambient vibrations facilitate this movement. The amount of energy generated by this approach fundamentally depends upon the quantity and form of the kinetic energy available in the application environment and the efficiency of the generator and the power conversion electronics (Beeby et al., 2007). While knowledge about electromagnetism has existed for a long time, using the knowledge to create a micro energy generating devices has been a recent technical achievement (Beeby et al., 2006). These generators have a high energy density and can be fabricated into small sizes. One of the biggest technical challenges in this sector currently is enlarging the effective energy harvesting bandwidth (Wei & Jing, 2017). Vibration energy harvesting devices have found application in aircraft-based applications, sensors, wireless autonomous devices, biomedical implants, wristwatches and many more. The patents in this sector displayed an interdisciplinarity of *0.767.*

### 7.3.1 Sector Patent landscape

IPC H02K35 describes inventions involving generators with reciprocating, oscillating or vibrating coil systems, magnet, armature or other part of the magnetic circuit. Inductive vibration energy harvesting technologies fall within this category. In terms of patenting activity, this IPC is the smallest amongst the three sectors studied in this research, with just over 5000 patent publications till date. The first publication appeared in 1904 and was filed in France. In the next 47 years an average of 3 patents were published per year. The research activity between 1970 and 2000 may be described as turbulent with many peaks and valleys seen in the patenting activity (Figure 7-5). Beyond 2000 a steady growth of 17% per year can be seen in this IPC leading to the publishing of 81% of the total patents till date.

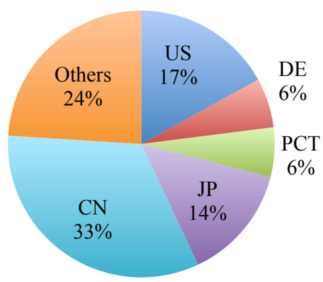
While these publications come from 62 different countries, the largest contributors are US, Japan, Germany and China. Together these countries produced 70% of the total patents (Figure 7-6). Amongst these four, China occupies the top position with 33% of the total patents. Patenting activity started in late 1980s in this country but has seen a steady growth rate of 22% in the last decade. The US occupies the second position with a share of 17% of the patents. Japan holds the third position with 14% of the patents, followed by Germany with 6%.

**Figure 7-5 Patenting activity of IPC H02K35**




The assignee landscape looks flat and there does not seem to be a single dominant player yet. This may indicate that the market in this sector is still emerging. Brothers Industries Ltd. hold the highest number of patents in this IPC, which amounts to about 0.8% of the total patents in this sector. Samsung Electro-Mechanics and Panasonic Corporation occupy the next two positions with 0.6% and 0.5% of the total patents respectively. About 13% of the total patents come from research organizations. This may indicate that the technology is still at a developmental stage. Chinese research organizations dominate the arena. The top 10 research organizations that own 23% of the patents from this category are all based in China.

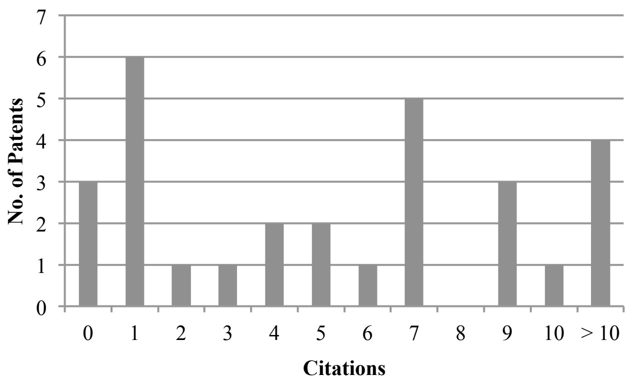
**Figure 7-6: International distribution of patenting activity in IPC H02K35**



### 7.3.2 Data Description

I shortlisted 29 samples from this sector based on the process described in CHAPTER 6. The descriptive statistics of the samples is given in TABLE 8-4. On an average, these samples have accrued 5 citations (SD = 4.7) in the first 5 years of their life and have cited 12 references. The inventor team size of the samples in this sector is the smallest with 58% being invented by a sole inventor. 41% of the inventions have been protected in more than 2 jurisdictions while 48% have been filed for protection only in the US. The citation distribution of the sample set is given in Figure 7-7. 52% of the samples have less than 6 citations and only 4 samples (14%) have greater than 10 citations. The average processing time for these patents was 2 years (SD = 1.03).

**Figure 7-7: Citation Distribution of IV Samples**




These 29 patents are held by 22 different assignees. Out of these 22 assignees, 61% are corporate entities, 17% are research organizations and the remaining are individual inventors. Excluding the individual inventors, 52% of the assignees are US organizations while the remaining 26% is shared by Japanese and British organizations. Further information on 8 of the assignees, which includes 5 individual inventors and 3 organizations, could not be obtained. Additional details of the remaining assignees are given in TABLE 7-6. Out of the remaining 11 assignees 7 are publicly held organizations while 4 are privately held. The financial details of the private organization could not be verified. The financial information of the publicly held organizations is given in TABLE 7-6. The details reveal that these organizations may be classified as large size.

## 7.4 Piezoelectric Energy Harvesting

In PZ energy harvesting, mechanical strain energy is transformed into electrical energy through the use of piezoelectric materials. A piezoelectric device requires an external stress in the form of compression or vibration, to function. Most piezoelectric energy harvesters are in the form of cantilevered beams with one or two piezoceramic layers. The harvester beam is located on a vibrating host structure and the strain induced in the piezoceramic layers results in an alternative voltage output across their electrodes (Erturk & Inman, 2011). The earliest PZ devices extracted energy from impact (Beeby et al., 2006). These generators are unaffected by external electromagnetic waves thus, enabling the construction of both micro-scale and macro-scale devices. However, the technological challenges include depolarization and poor coupling in piezo-film (Wei & Jing, 2017). There has been an increased interest in this technology since early 2000s. Compared to other two commonly used energy harvesting techniques (electromagenetic and electrostatic), piezoelectric technique has received the most attention amongst researchers (Erturk & Inman, 2011).

Piezoelectric energy harvesting devices find application in railways, lighters and other electrical, aerospace, vehicle sensors, remote controls, healthcare and toys and gadgets. These generators have simple structures, which makes their application easier. For example, installation of these devices on roads and rail networks provides the opportunity to generate electricity every time a vehicle passes overhead. This electricity can then be used to power traffic lights. IDTechEx (2012) note that the money invested on piezoelectric energy harvesting will grow to $145 million in 2018 and create a $667 million market by 2022. This sector ranks third in terms of interdisciplinarity of the four chosen sectors *(HHI = 0.844)*.

### 7.4.1 Sector Patent landscape

IPCs H01L41 and H02N2 generally classify patents belonging to PZ sector. Hence, I investigate the patenting activity in these classifications. Figure 8-8 shows the patenting trend in this sector in the last 90 years. Patent activity in these areas started in early 1920s with the earliest patent published in 1922. A scattered distribution of patenting activity could be seen in the following few decades that later grew by an average of 19% per year between 1950-1970. From 1970s onwards, there was an increased interest in this sector. The number of patent publications in this decade alone was more than 9 times that of all the publications until then. This period also coincides with the coming of modern computing, microprocessors and general boom in science and technology. After a slight decline in numbers of publications between 1980-1990, the patenting activity has been growing steadily by an average of more than 100% per decade. The dip in the patenting activity could be a result of global economic recession, the repercussions of which lasted for close to a decade in many countries.

The US was the leader in this space until 1970s. Japan entered this sector much later than many countries such as US, Germany, France and UK. The first Japanese patent was published in 1964. However, Japan quickly took over the race and now accounts for 40% of the total patent publications till date in this sector. This country has been producing patent publications at an average of about 700 per year since 1970. The US now occupies the second position with 22% share of the patent publications. Figure 7-9 shows the distribution of the patent publications by country.

**Figure 7-8: Patenting activity of IPC H01L41**

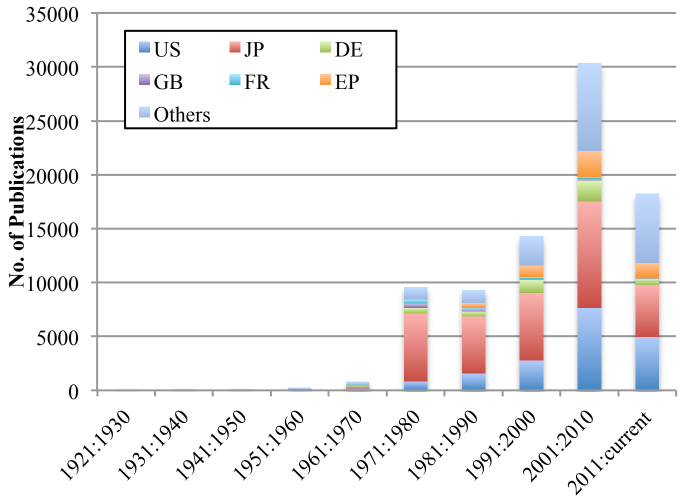
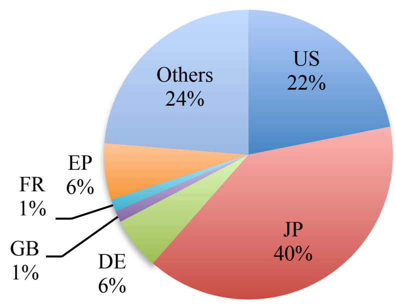



**Figure 7-9: International distribution of patenting activity in IPC H01L41**




The top 20 applicants in this sector own 41% of the patents, with Japanese corporates dominating the arena. Matsushita Electric Industrial Co. Ltd., which was renamed as Panasonic Corporation in 2008, owns 7% of the total patents in this sector. The first publication filed by this company was published in 1966. Since then the company has been filing for patents at an average rate of 22 applications per year. Murata Manufacturing Company is a close runner-up, owning 6% of the patents. Figure 8-10 shows the patenting activity of the top 10 applicants in this field between 1964-2000. About 1.8% of the inventions originate from universities and research organizations.

**Figure 7-10: Patenting activity of the top 10 applicants in IPC H01L41.**

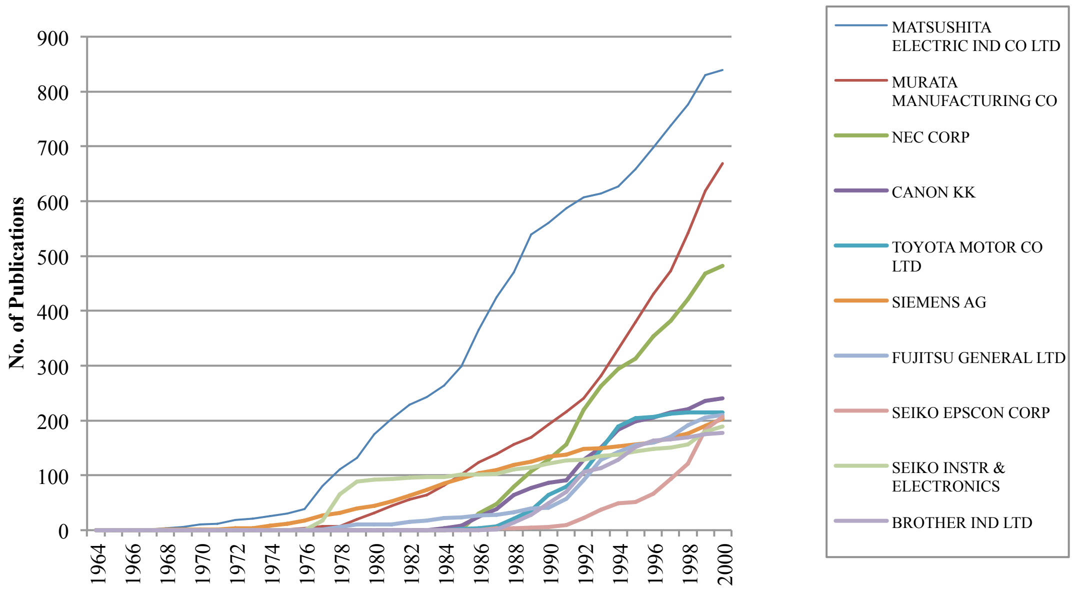
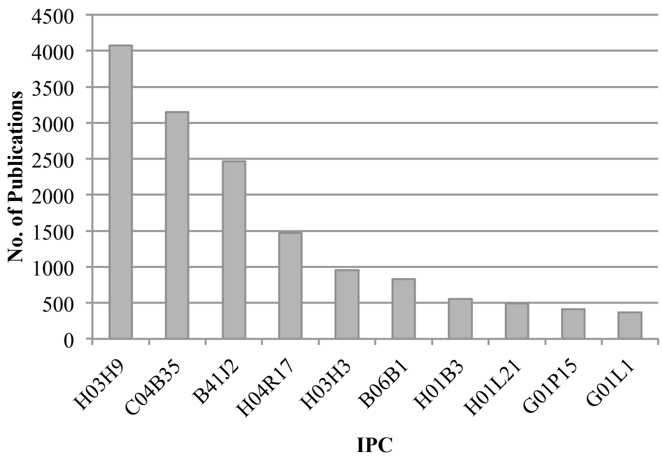



**Figure 7-11: Top 10 IPC classifications other than H01L41 and H02N2 of PZ patents**




After H01L41 and H02N2, the top 10 classifications assigned to these patents are given in Figure 7-11. According to these classifications, the main patented content are electromechanical resonators (H03H9), ceramic products and their compositions (C04B35), typewriters or selective printing mechanisms (B41J2), piezoelectric transducers (H04R17), resonating circuits (H03H3), apparatus for generating mechanical vibrations (B06B1), insulating bodies (H01B3) and treatment of semiconductor or solid state devices (H01L21).

### 7.4.2 Data Description

I shortlisted 53 patents from PZ sector published between 1989-1991 for analysis. Details and descriptive statistics of the samples of PZ sector are given in TABLE 7-7 and TABLE 7-8 respectively. These samples have an average processing time of 1.6 years (SD = 0.634) and on an average has an inventor team size of 2. As shown in Figure 7-12, 89% of the samples have less than 55 citations. 36% of the samples have been filed in only one jurisdiction (Figure 8-13) and 17% have been filed in more than 5 jurisdictions.

**Figure 7-12: Citation Distribution of PZ Samples**

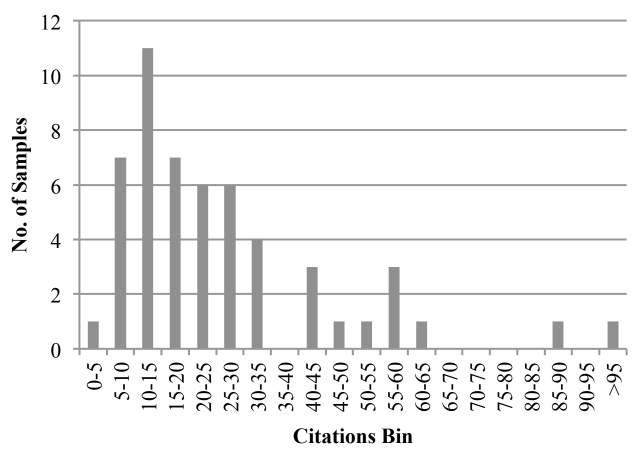
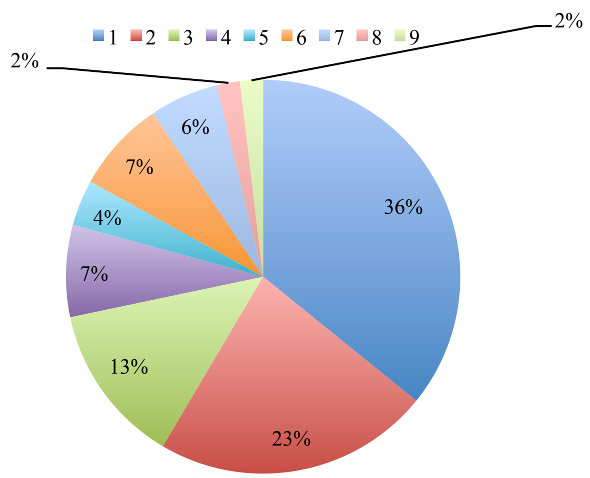



**Figure 7-13: Family Size Distribution of PZ Samples**




These 53 samples are owned by 38 different assignees with 12 assignees holding 52% of the patents. The assignees come from 5 different geographical locations; 49% from Japan, 40% from the US, and the UK, Soviet Union, and Austria together sharing the remaining 11%. Out of the 38 assignees, 28 (74%) are corporate organizations and 13% are research organizations, 2 of which are government organizations and 3 are private research institutions. Individual inventors amount to 11% of the total assignees. Details regarding the organizational status of one of the assignee could not be verified. The corporate organizations had been in operations for an average of 49 years when they filed for the patents contained in my dataset. The oldest of these assignees is NEC Corporation, which was established in 1899. Out of the 28 corporate organizations, financial details of 19 organizations is given in TABLE 7-9. The majority of these assignees may be classified as large corporations with presence across the globe with multi million dollars reported revenue.

## 7.5 Carbon Nanotubes

CNTs are allotropes of carbon with a cylindrical structure. These nanomaterials are known to have unique properties valuable for many fields such as electronics, optics, healthcare, etc. Due to their excellent electrical properties, they have been gathering interest in energy storage and energy harvesting applications (Kotipalli et al., 2010; Li et al., 2011; Li et al., 2010; Umeyama & Imahori, 2008). Single walled carbon nanotubes have been shown to increase the efficiency of solar panels (Li et al., 2009; Molinaro, 2007).

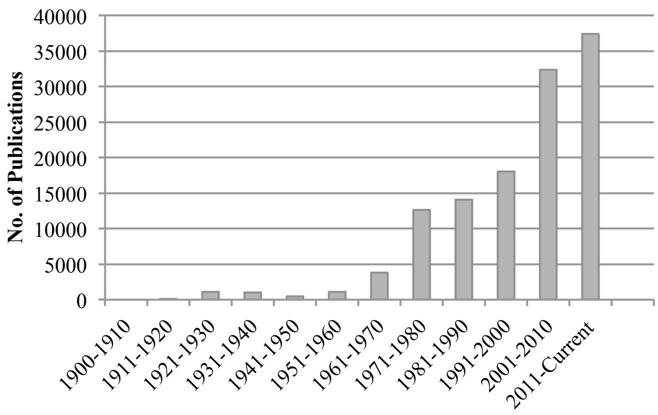
While several techniques for the synthesis of CNTs have been developed, the most common ones are the chemical vapour deposition (CVD) technique, the laser-ablation technique and the carbon arc discharge technique. This is followed by a purification process, which involves the removal of large graphite particles, amorphous carbon and any catalyst particles. The large-scale production and purification of the nanotubes still remains challenging. Other technical challenges of this technology are homogeneity of the material and presence of residual materials in the produced material (Eatemadi et al., 2014).

Though discovered just a few decades ago, research in CNT picked up due to its potential applications and the revolutionary improvements in existing technology that it promises. A study on nanotechnology patenting trends by Dang et al. (2010) found that between 1981-2008, IPC C01B (which include carbon nanotubes) ranked in the top 5 of the nanotechnology patent applications worldwide. An analysis of the technology areas showed that in applications filed in China in 2008, which ranked second in worldwide nanotechnology patent applications, “carbon nanotube” was a highly-mentioned topic. Golnabi (2012) notes that in CNT research, the US, Japan, Germany and China together have a paper publication contribution of 67% of the total with the US in the leading position. The author also notes that the annual growth rate of patents is higher (8.68%) than that of journal papers (8.09%) indicating that there is a higher tendency towards application of CNTs rather than basic research. The growing demand from applications, such as advanced materials, electronics & semiconductors, chemical & polymers, batteries & capacitors, energy, aerospace & defense, and medical is expected to fuel the growth of the carbon nanotube market. Forecasters expect the market for this technology to reach $8.7 Billion by 2022 (Wire, 2017). Of the four sectors, CNT is the most interdisciplinary *(HHI = 0.866).*

### 7.5.1 Sector Patent landscape

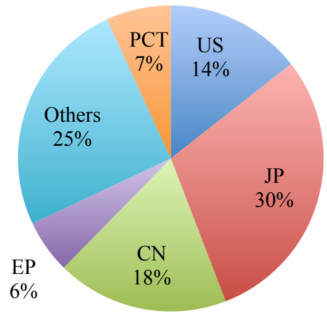
Due to the gaining importance of carbon nanotubes, many scholars have studied the patent landscape of this sector. For example, Harris and Bawa (2007) studied CNT landscape around nanomedicine application, while Tannock (2012) researched the differences in patenting activity of research organizations. The patent data for these landscapes was derived through specific keywords pertaining to CNT technology. In contrast, I assess the landscape of the whole IPC of which CNT technology is a part. This approach enables one to visualise the complete background knowledge that has eventually led to this technology. IPC C01B31 and D01F9 describe technologies pertaining to Carbon, its compounds, man-made filaments and their manufacturing. These classes are also used to categorise inventions related to carbon nanotubes.

**Figure 7-14: Patenting activity of IPCs C01B31 and D01F9**




The patenting activity in this sector picked up after 1970s ( Figure 7-14) and has seen an average year-on-year growth of 8% in the last 15 years. Though the patenting activity in Japan started in 1970s, it soon picked up and currently dominates the landscape. The Japanese patents in this sector account for 30% of all the patents (Figure 8-15)). Patenting in this country increased by an average of 2% each year, since 2002. China marks the second place owning 18% of the total patents. While the first Chinese patent was published in 1985, it has soon caught up with the other countries. Patenting activity of China has been the most aggressive of all the countries with a remarkable 25% year-on-year growth. The US occupies the third position with 14% of all the patents in these IPCs. Growth rate of patents in this country has been a modest 5% since early 2000s.

**Figure 7-15: International distribution of patenting activity in IPCs C01B31 and D01F9**




### 7.5.2 Data Description

I shortlisted 25 patents from CNT sector published between 2000-2002 for analysis. Details and descriptive statistics of the samples are given in TABLE 8-10 and respectively. These samples have an average processing time of 2.4 years (SD = 0.86) and on an average have an inventor team size of 3. As shown in Figure 8-16, 60% of the samples have received less than 100 citations. These samples have an average family size (INPADOC) of 5. This indicates that the invention has been filed for protection in 5 jurisdictions. About 72% of the samples have also been filed for protection in Japan and 48% in Europe. Other jurisdictions include Taiwan (8%), South Korea (24%), Germany (20%), Canada (24%), Australia (20%), Austria (12%), China (20%), Denmark (4%), Russian Federation (4%), Spain (4%), France (4%), Norway (4%) and Portugal (4%) (Figure 8-17). Thus, it may be concluded that the inventors of these patents consider Japan and Europe as favourable markets for CNT technology next to US. Out of the 25 samples, 7 samples have multiple applications in the US. This indicates that theses inventions are part of similar group of technologies that have been further developed by its inventors. These 25 samples are owned by 25 different assignees where 44% of them are corporate bodies, 52% are research organizations and 4% belong to individual inventor. The assignees come from 4 different geographical locations: 24% from Japan, 56% from the US, and 4% from France and the remaining from South Korea. 12% of the samples are an outcome of joint venture between a corporate and a research organization. As compared to the samples of PZ sector, more samples from this sector come from research organizations, which indicates that this technology is at a developmentally nascent position as compared to PZ technology. Moreover 77% of these research organizations are based in the US.

**Figure 7-16: Citation distribution of CNT samples**

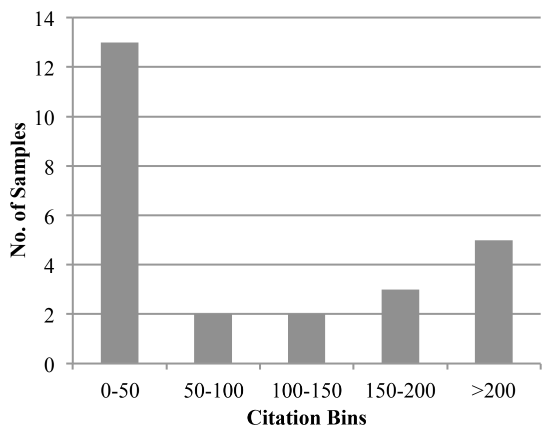
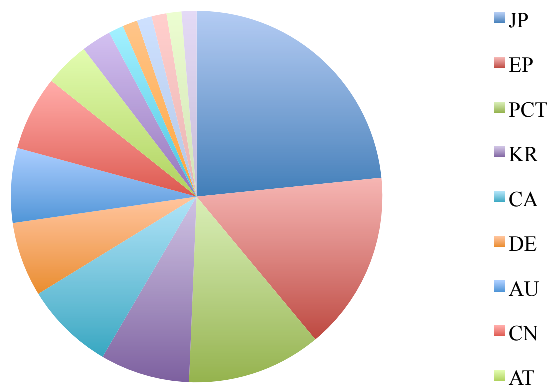



**Figure 7-17: Family distribution of CNT samples**




Unlike in the PZ sector, the corporate organizations from this sector are of various sizes. Out of the 11 corporate assignees, the number of private and publicly traded companies is evenly distributed. The corporate status of 1 assignee could not be verified. All the publicly traded companies may be classified as large multinational companies with multimillion dollar reported revenues. The financial details have been taken from the corporate websites, annual reports, financial websites such as Bloomberg.com and general Internet search (TABLE 8-12). The revenue details of the privately held companies could not be obtained. The oldest of these corporate organizations is DuPont, which was established in 1802 and had been in operation for approximately 198 years when the patents in this dataset were filed. The research organizations, on an average had been in operation for 75 years when the patents in this dataset were filed.

It may be seen from the sample descriptions that the patents in the dataset do not belong to any specific single geographical region or type of organization. This excludes the possibility that the patent value may be influenced by factors other than knowledge structure, such as the type of the organization, its geographical location etc. Also, the distribution of assignee size (in terms of revenue or market cap) is similar in all the sectors. Thus, the effect of corporate size on the technical value of the inventions, if any, would be similar in all the inventions.

## TABLE 7-1: TFP Sector Sample Details

| Patent No. | Title | Filing Date | Grant Date | Assignor | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US4892592 | Thin Film Semiconductor Solar Cell Array And Method Of Making | 8/11/1988 | 9/01/1990 | SOLAREX CORP [US] | 80 | 9 | 1 |
| US4900369 | Solar Cell | 14/12/1988 | 13/02/1990 | NUKEM GMBH [DE] | 25 | 13 | 18 |
| US4909857 | Electrodeposited Doped II-VI Semiconductor Films And Devices Incorporating Such Films | 21/12/1988 | 20/03/1990 | STANDARD OIL CO | 6 | 17 | 1 |
| US4910412 | Light Biased Photoresponsive Array | 17/04/1989 | 20/03/1990 | STEMCOR CORP | 7 | 13 | 1 |
| US4914044 | Method Of Making Tandem Solar Cell Module | 18/07/1988 | 3/04/1990 | SIEMENS AG | 19 | 6 | 3 |
| US4915744 | High Efficiency Solar Cell | 3/02/1989 | 10/04/1990 | APPLIED SOLAR ENERGY CORP [US] | 2 | 2 | 4 |
| US4915745 | Thin Film Solar Cell And Method Of Making | 22/09/1988 | 10/04/1990 | ATLANTIC RICHFIELD CO | 182 | 7 | 4 |
| US4920067 | Process For II-VI Compound Epitaxy | 5/10/1988 | 24/04/1990 | KNAPP JAMIE | 2 | 14 | 2 |
| US4929281 | Method For Producing Thin-Film Solar Cells In A Series-Connected Array | 31/03/1988 | 29/05/1990 | NUKEM GMBH | 14 | 6 | 7 |
| US4931412 | Method Of Producing A Thin Film Solar Cell Having A N-I-P Structure | 21/06/1988 | 5/06/1990 | LICENTIA GMBH [DE] | 26 | 15 | 4 |
| US4935067 | Solar Cell And Fabrication Method Thereof | 31/01/1989 | 19/06/1990 | MITSUBISHI ELECTRIC CORP [JP] | 8 | 3 | 4 |
| US4936924 | Thin-Film Solar Battery And Its Manufacturing Method | 16/08/1988 | 26/06/1990 | MITSUBISHI ELECTRIC CORP [JP] | 10 | 6 | 3 |
| US4948436 | Thin-Film Solar Cell Arrangement | 23/12/1988 | 14/08/1990 | SIEMENS AG | 43 | 10 | 3 |
| US4950615 | Method And Making Group IIB Metal - Telluride Films And Solar Cells | 6/02/1989 | 21/08/1990 | INT SOLAR ELECTRIC TECHNOLOGY | 99 | 12 | 1 |
| US4956685 | Thin Film Solar Cell Having A Concave N-I-P Structure | 13/02/1990 | 11/09/1990 | LICENTIA GMBH | 13 | 10 | 1 |
| US4968384 | Method Of Producing Carbon-Doped Amorphous Silicon Thin Film | 14/09/1989 | 6/11/1990 | FUJI ELECTRIC RES | 22 | 1 | 2 |
| US4971633 | Photovoltaic Cell Assembly | 26/09/1989 | 20/11/1990 | US ENERGY | 10 | 11 | 1 |
| US4997491 | Solar Cell And A Production Method Therefor | 15/11/1989 | 5/03/1991 | MITSUBISHI ELECTRIC CORP [JP] | 29 | 9 | 8 |
| US5009719 | Tandem Solar Cell | 8/11/1989 | 23/04/1991 | MITSUBISHI ELECTRIC CORP [JP] | 64 | 10 | 3 |
| US5019177 | Monolithic Tandem Solar Cell | 3/11/1989 | 28/05/1991 | US ENERGY [US] | 112 | 8 | 7 |
| US5021100 | Tandem Solar Cell | 12/12/1989 | 4/06/1991 | MITSUBISHI ELECTRIC CORP [JP] | 68 | 6 | 2 |
| US5022930 | Thin Film Photovoltaic Panel And Method | 20/06/1989 | 11/06/1991 | PHOTON ENERGY INC | 83 | 7 | 5 |

| Patent No. | Title | Filing Date | Grant Date | Assignor | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US5028274 | Group I-III-VI2 Semiconductor Films For Solar Cell Application | 7/06/1989 | 2/07/1991 | INT SOLAR ELECTRIC TECHNOLOGY | 128 | 6 | 2 |
| US5034333 | Method Of Manufacturing An Amorphous Silicon Solar Cell | 26/10/1989 | 23/07/1991 | SAMSUNG ELECTRONIC DEVICES [KR] | 15 | 5 | 3 |
| US5035753 | Photoelectric Conversion Device | 22/12/1989 | 30/07/1991 | SEMICONDUCTO R ENERGY LAB [JP] | 8 | 4 | 2 |
| US5045409 | Process For Making Thin Film Solar Cell | 17/11/1988 | 3/09/1991 | ATLANTIC RICHFIELD CO | 150 | 6 | 1 |
| US5047090 | Semiconductor Device | 14/02/1990 | 10/09/1991 | AGENCY IND SCIENCE TECHN [JP]; MATSUSHITA ELECTRIC WORKS LTD [JP] | 16 | 5 | 4 |
| US5057163 | Deposited-Silicon Film Solar Cell | 4/05/1988 | 15/10/1991 | ASTROPOWER INC [US] | 85 | 7 | 5 |
| US5059254 | Solar Cell Substrate And Solar Panel For Automobile | 24/05/1989 | 22/10/1991 | ASAHI GLASS CO LTD [JP] | 85 | 9 | 7 |
| US5061322 | Method Of Producing P-Type Amorphous Silicon Carbide And Solar Cell Including Same | 18/09/1989 | 29/10/1991 | FUJI ELECTRIC CORP RESEARCH AN | 20 | 3 | 2 |
| US5071490 | Tandem Stacked Amorphous Solar Cell Device | 30/04/1990 | 10/12/1991 | SHARP KK [JP] | 62 | 4 | 2 |
| US5078804 | I-III-VI2 Based Solar Cell Utilizing The Structure Cuingase2cdzns/Zno | 17/08/1990 | 7/01/1992 | BOEING CO | 109 | 3 | 1 |
| US5085711 | Photovoltaic Device | 15/02/1990 | 4/02/1992 | SANYO ELECTRIC CO | 17 | 5 | 1 |
| US5100480 | Solar Cell And Method For Manufacturing The Same | 31/10/1990 | 31/03/1992 | MITSUBISHI ELECTRIC CORP [JP] | 79 | 12 | 4 |
| US5103268 | Semiconductor Device With Interfacial Electrode Layer | 8/07/1991 | 7/04/1992 | SIEMENS SOLAR IND LP [US] | 28 | 2 | 3 |
| US5104455 | Amorphous Semiconductor Solar Cell | 7/01/1991 | 14/04/1992 | SHARP KK [JP] | 19 | 3 | 3 |
| US5112410 | Cadmium Zinc Sulfide By Solution Growth | 7/08/1990 | 12/05/1992 | BOEING CO | 38 | 3 | 1 |
| US5123968 | Tandem Photovoltaic Solar Cell With III-V Diffused Junction Booster Cell | 19/06/1991 | 23/06/1992 | BOEING CO [US] | 58 | 7 | 11 |
| US5125984 | Induced Junction Chalcopyrite Solar Cell | 25/02/1991 | 30/06/1992 | SIEMENS AG [DE] | 118 | 3 | 3 |
| US5131954 | Monolithic Solar Cell Array And Method For Its Manufacturing | 25/11/1991 | 21/07/1992 | UNITED SOLAR SYSTEMS CORP | 81 | 13 | 2 |
| US5137835 | Method For Manufacturing A Chalcopyrite Solar Cell | 15/04/1991 | 11/08/1992 | SIEMENS AG [DE] | 71 | 5 | 3 |
| US5141564 | Mixed Ternary Heterojunction Solar Cell | 17/01/1991 | 25/08/1992 | BOEING CO | 122 | 14 | 1 |
| US5151255 | Method For Forming Window Material For Solar Cells And Method For Producing | 3/10/1990 | 29/09/1992 | MITSUI TOATSU CHEMICALS [JP] | 19 | 5 | 2 |

| Patent No. | Title | Filing Date | Grant Date | Assignor | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| | Amorphous Silicon Solar Cell | | | | | | |
| US5155565 | Method For Manufacturing An Amorphous Silicon Thin Film Solar Cell And Schottky Diode On A Common Substrate | 24/04/1990 | 13/10/1992 | MINNESOTA MINING & MFG | 24 | 59 | 1 |
| US5158618 | Photovoltaic Cells For Converting Light Energy To Electric Energy And Photoelectric Battery | 8/02/1991 | 27/10/1992 | BIOPHOTONICS INC [US] | 73 | 5 | 7 |

**TABLE 7-2: TFP Sample Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| **Citations** | 45 | 2.00 | 182.00 | 52 | 45.12135 |
| **References** | 45 | 1.00 | 59.00 | 9 | 8.66975 |
| **Family Size** | 45 | 1.00 | 18.00 | 3 | 3.15940 |
| **Claims** | 45 | 1.00 | 92.00 | 17 | 15.10843 |
| **Processing Time** | 45 | .60 | 3.40 | 1.60 | .53640 |
| **Inventors** | 45 | 1.00 | 8.00 | 3 | 1.64317 |
| **Valid N (listwise)** | 45 | | | | |

## TABLE 7-3: TFP Sample Assignee Details

| Assignor | Type | No. of Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| LICENTIA GMBH | C | 2 | Not Available | | |
| NUKEM GMBH | C | 2 | 1960 | NUKEM GmbH markets uranium products for customers in Germany and internationally. The company focuses on the civil nuclear fuel market. It buys and sells uranium in the form of U308, uranium hexafluoride, and enriched uranium products that are used to produce fuel for commercial nuclear reactors. The company also provides fabrication services; and uranium for research reactors. It serves nuclear utilities; and producers managing temporary shortfalls, as well as investors, such as hedge funds, mutual funds, and other intermediaries. | USD 19.3 M revenue in 2015 |
| SIEMENS AG | C | 4 | 1847 | Siemens AG is an engineering and manufacturing company. The Company focuses on areas of electrification, automation, and digitalization. Siemens also provides engineering solutions in automation and control, power, transportation, and medical diagnosis. | EUR 83.05 B revenue in 2017 |
| AGENCY IND SCIENCE TECHN [JP]; MATSUSHITA ELECTRIC WORKS LTD [JP] | C-R | 1 | Joint Venture | | |
| ASAHI GLASS CO LTD [JP] | C | 1 | 1907 | Asahi Glass Co., Ltd. manufactures and sells glass, electronics, chemicals, and ceramics/other products worldwide. The company offers architectural glass products, including float glass, low-emissivity glass, double glazing glass for solar control/heat-insulation, safety glass, and decorative glass; insulating, laminated, wired, toughened, solar control, sound insulation, decorative, float and patterned, structural glazing, and industrial glasses; and tempered and laminated automotive glasses. It also provides glass substrates used for thin-film-transistor liquid crystal displays and OLEDs. Further, it provides refractory materials, fine ceramics, and sputtering targets; and logistics/engineering services. | JYP 1.4 M net sales |
| FUJI ELECTRIC ADVANCED TECHNOLOGY CO LTD | C | 2 | | Fuji Electric Advanced Technology Co. Ltd. Was the Fuji Electric Holdings Company's R&D Company. This was converted into a holding company in 2009. | Not Available |
| MITSUBISHI ELECTRIC CORP [JP] | C | 6 | 1921 | Mitsubishi Electric is one of the world's leading names in the manufacture and sales of electrical and electronic products and systems used in a broad range of fields and applications. Product sectors include energy and electric systems, industrial automation systems, information and communication systems, electronic devices, home appliances and others. | JYP 4.3 T net sales in 2017 |
| MITSUI TOATSU CHEMICAL [JP] | C | 1 | 1968 | Mitsui Toatsu Chemicals, Inc. was formed in 1968 through the merger of two Mitsui group firms, Toyo Koatsu and Mitsui Chemical. The Company manufactures agrochemicals, pharmaceuticals, biochemicals, functional resins and electronic materials | Not Available |
| SANYO ELECTRIC CO | C | 1 | 1947 | SANYO Electric Co., Ltd. develops, manufactures, and sells electronic equipment worldwide. The company provides business solutions, which include communication solutions, security systems, personal computers, professional AV solutions, document and imaging solutions, terminal solutions, information technology solutions, recording media, and video intercom systems. It also offers industrial devices, which include capacitors, sensors, batteries, electronic materials, resistors, thermal management solutions, EMC components and circuit protection, factory automation and welding machines, inductors (coils), input devices, industrial devices, recording media, motors, compressors, custom and module devices, materials, semiconductors, relays, connectors, automotive, and industrial infrastructure; eco-solutions, including photovoltaic modules, lighting products, electrical construction materials, air conditioning and purification equipment, and home building products and materials; and medical devices. Currently SANYO Electric Co., Ltd. operates as a subsidiary of Panasonic Corporation. | Not Available |

| Assignor | Type | No. of Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| SEMICONDUCTOR ENERGY LAB [JP] | R | 1 | 1980 | Semiconductor Energy Laboratory Co. Ltd. Operates in the area of R&D of transistors and semiconductor devices using oxide semiconductors; R&D of materials and devices for liquid crystal, EL, and batteries; R&D of display devices using them, and R&D of integrated circuits and rechargeable batteries. Patenting of inventions and exercising of patent rights. | USD 38 M net capital |
| SHARP KK [JP] | C | 2 | 1912 | Sharp Corporation manufactures and sells electronic communication equipment, electronic equipment, electronic application equipment, and electronic components in Japan, The Americas, Europe, China, and internationally. The company operates through five segments: Consumer Electronics, Energy Solutions, Business Solutions, Electronic Components and Devices, and Display Devices. | JYP 2.05 T net revenue 2017 |
| SAMSUNG ELECTRONIC DEVICES [KR] | C | 1 | 1969 | Samsung Electronics Co., Ltd. manufactures a wide range of consumer and industrial electronic equipment and products such as semiconductors, personal computers, peripherals, monitors, televisions, and home appliances including air conditioners and microwave ovens. The Company also produces Internet access network systems and telecommunications equipment including mobile phones. | KRW 239.58 T revenue in 2017 |
| APPLIED SOLAR ENERGY CORP [US] | C | 1 | | Applied Solar is a major supplier of solar cells, panels and solar arrays to NASA, the DoD and commercial spacecraft programs. | Not Available |
| ASTROPOWER INC [US] | C | 1 | | The Company develops, manufactures, markets and sells PV solar cells, modules and panels for generating solar electric power. The company filed for bankruptcy in 2004. | NA |
| ATLANTIC RICHFIELD CO | C | 2 | 1966 | The Atlantic Richfield Company was created in 1966 by the merger of Richfield Oil Corporation and Atlantic Refining Company. | USD10.3 B sales in 1998 |
| BIOPHOTONICS INC [US] | C | 1 | Not Available | | |
| BOEING CO | C | 4 | 1916 | Boeing is the world's largest aerospace company and leading manufacturer of commercial jetliners, defense, space and security systems, and service provider of aftermarket support. Boeing products and tailored services include commercial and military aircraft, satellites, weapons, electronic and defense systems, launch systems, advanced information and communication systems, and performance-based logistics and training. | USD 93.93B Revenue |
| INT SOLAR ELECTRIC TECHNOLOGY | C | 2 | 1985 | International Solar Electric Technology, Inc. develops materials and processes for manufacturing photovoltaic modules. Its product includes copper indium gallium selenide modules (CIGS) solar cells and modules for residential, commercial, and utility projects. The company provides solar cell processing, research and development, technology licensing, and system design and installation services. | Private Company |
| KNAPP JAMIE | I | 1 | Not Applicable | | |
| MINNESOTA MINING & MFG | C | 1 | 1902 | Minnesota Mining And Manufacturing Company of Wisconsin offers commercial services. The Company provides cleaning, abrasives, splinting, filtration, pet care, construction, touch display, and dental products to health care, automotive, electronic, and transportation industries. Minnesota Mining And Manufacturing serves customers worldwide. | USD 4.85 B revenue in 2017 |
| PHOTON ENERGY INC | C | 1 | Not Available | | |
| SIEMENS SOLAR IND LP [US] | C | 1 | | Siemens Solar Industries L.P, headquartered in Camarillo, Calif., is a member of the Siemens Solar Group. The current status of the company is unknown. Siemens shut down its solar business in 2012 due to losses. | Not Available |
| SOLAREX CORP [US] | C | 1 | 1973 | Solarex was the largest producer and developer of polycrystalline solar cells. Amoco took over Solarex in 1983. | Not Available |
| STANDARD OIL CO | C | 1 | 1870 | Standard Oil Co. Inc. was an American oil producing, transporting, refining, and marketing company. In 1911 the company was dissolved under the Sherman Antitrust Act and split into 34 companies. | Not Available |
| STEMCOR CORP | C | 1 | Not Available | | |
| UNITED SOLAR SYSTEMS | C | 1 | 1990 | United Solar Ovonic Corp. was formerly known as United Solar Systems Corp, was a manufacturer of flexible thin-film amorphous silicon alloy multi-junction solar cells and related products. On August | Not Available |

| Assignor | Type | No. of Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| CORP | | | | 28, 2012, United Solar Ovonic Corp. went out of business as per its Chapter 11 liquidation filing under bankruptcy. | |
| US Department of ENERGY | R | 2 | 1977 | The United States Department of Energy (DOE) is a cabinet-level department of the United States Government concerned with the United States' policies regarding energy and safety in handling nuclear material. Its responsibilities include the nation's nuclear weapons program, nuclear reactor production for the United States Navy, energy conservation, energy-related research, radioactive waste disposal, and domestic energy production. | Not Applicable |

*C=Corporate*

*I=Individual*

*R=Research Organization*

*M=Million*

*B=Billion*

*T=Trillion*

*USD=US Dollars*

*JPY=Japanese Yen*

*KRW = Korean Republic Won*

## TABLE 7-4: IV Sector Sample Details

| Patent No. | Title | Filing Date | Grant Date | Assignee | 5-Year Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US4806805 | Electrical energy generating system utilizing a moving vehicle | 20/07/1987 | 21/02/1989 | PINCHEFSKY BARRY [US] | 0 | 9 | 1 |
| US4827163 | Monocoil reciprocating permanent magnet electric machine with self-centering force | 4/03/1986 | 2/05/1989 | MECHANICAL TECH INC [US] | 5 | 7 | 1 |
| US4924123 | Linear generator | 16/12/1988 | 8/05/1990 | AISIN SEIKI JP]; TOYODA CHUO KENKYUSHO KK [JP] | 6 | 7 | 2 |
| US4937481 | Permanent magnet linear electromagnetic machine | 13/01/1989 | 26/06/1990 | MECHANICAL TECH INC [US] | 15 | 3 | 3 |
| US5038061 | Linear actuator/motor | 25/05/1990 | 6/08/1991 | OLSEN JOHN H [US] | 1 | 22 | 1 |
| US5151695 | Telemetric measuring device with high power generation | 2/10/1990 | 29/09/1992 | SOUTHWEST RES INST [US] | 2 | 8 | 1 |
| US5175457 | Linear motor or alternator plunger configuration using variable magnetic properties for center row and outer rows of magnets | 28/10/1991 | 29/12/1992 | MECHANICAL TECH INC [US] | 4 | 6 | 1 |
| US5180939 | Mechanically commutated linear alternator | 24/02/1992 | 19/01/1993 | CUMMINS POWER GENERATION INC [US] | 3 | 1 | 1 |
| US5347186 | Linear motion electric power generator | 26/05/1992 | 13/09/1994 | MCQ ASSOCIATES INC [US]; KAB LAB INC [US] | 9 | 8 | 1 |
| US5696413 | Reciprocating electric generator | 24/10/1994 | 9/12/1997 | AQUA MAGNETICS INC [US] | 4 | 15 | 1 |
| US5818132 | Linear motion electric power generator | 13/01/1997 | 6/10/1998 | KONOTCHICK, JOHN A | 13 | 5 | 4 |
| US6291901 | Electrical power generating tire system | 13/06/2000 | 18/09/2001 | CEFO NEVRES | 10 | 18 | 1 |
| US6369469 | Poly phase linear alternator | 26/07/2000 | 9/04/2002 | MURRAY LAWRENCE D | 1 | 8 | 1 |

| Patent No. | Title | Filing Date | Grant Date | Assignee | 5-Year Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US6628019 | HIGH EFFICIENCY PNEUMATICALLY DRIVEN ELECTRIC POWER GENERATOR | 21/07/1999 | 25/04/2002 | CARROLL JOHN B, ; WESTINGHOUSE AIR BRAKE TECHNOLOGIES CORPORATION | 0 | 13 | 5 |
| US6798090 | Electrical power generation by coupled magnets | 18/04/2002 | 23/10/2003 | INNOVATIVE TECH LICENSING LLC [US] | 9 | 34 | 1 |
| US6930414 | Linear electrodynamic system and method | 14/10/2003 | 16/08/2005 | STIRLING TECHNOLOGY CO [US] | 1 | 5 | 1 |
| US7009315 | Apparatus for converting vibration energy into electric power | 19/04/2002 | 21/11/2002 | SEIKI EPSON CORP [JP] | 7 | 7 | 4 |
| US7184363 | Buoyant container with wave generated power production | 10/01/2005 | 4/08/2005 | SZEGEDI NICHOLAS J, ; HAVELKA STEVEN E, ; NORTHROP GRUMMAN CORPORATION | 7 | 8 | 5 |
| US7391135 | Electromagnetic energy converter | 6/10/2005 | 27/04/2006 | ENOCEAN GMBH [DE] | 0 | 16 | 5 |
| US7479715 | Omnidirectional Electrical Generators | 14/08/2006 | 14/02/2008 | INCELEX LLC [US] | 1 | 4 | 1 |
| US7535148 | Electromagnetic device for converting mechanical vibrational energy into electrical energy, and manufacture thereof | 13/08/2004 | 11/01/2007 | UNIVERSITY OF SOUTHAMPTON | 9 | 19 | 4 |
| US7554224 | Electromechanical generator for converting mechanical vibrational energy into electrical energy | 22/02/2006 | 23/08/2007 | PERPETUUM LTD [GB] | 7 | 15 | 7 |
| US7579757 | Method and Micro Power Generator For Generating Electrical Power From Low Frequency Vibrational Energy | 21/01/2005 | 12/06/2008 | UNIV MICHIGAN [US] | 11 | 7 | 1 |
| US7586220 | Electromechanical Generator for Converting Mechanical | 1/10/2007 | 30/10/2008 | PERPETUUM LTD [GB] | 7 | 17 | 5 |

| Patent No. | Title | Filing Date | Grant Date | Assignee | 5-Year Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| | Vibrational Energy Into Electrical Energy | | | | | | |
| US7795763 | Electromagnetic Device For Converting Mechanical Vibrational Energy Into Electrical Energy | 23/03/2005 | 9/10/2008 | UNIV SOUTHAMPTON [GB] | 11 | 48 | 6 |
| US7843090 | Electromechanical Generator for Converting Mechanical Vibrational Energy Into Electrical Energy | 8/08/2006 | 15/07/2010 | PERPETUUM LTD [GB] | 1 | 9 | 5 |
| US7999402 | Electromechanical Generator for Converting Mechanical Vibrational Energy Into Electrical Energy | 3/10/2006 | 3/09/2009 | PERPETUUM LTD [GB] | 5 | 23 | 3 |
| US8080906 | Generator For Converting Mechanical Vibrational Energy Into Electrical Energy | 11/04/2006 | 13/11/2008 | PERPETUUM LTD [GB] | 7 | 14 | 5 |
| US8115350 | 1. Oscillation type electromagnetic power generator and method for manufacturing oscillation type electromagnetic power generator | 20/09/2007 | 14/02/2012 | SUMIDA CORP [JP] | 1 | 12 | 6 |

**TABLE 7-5: IV Sample Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| **Citations** | 29 | 0 | 15 | 5 | 4.27215 |
| **References** | 29 | 1 | 48 | 13 | 9.85286 |
| **Family Size** | 29 | 1 | 7 | 3 | 2.04807 |
| **Claims** | 29 | 4 | 53 | 16 | 10.56134 |
| **Processing Time** | 29 | 0.6 | 4.4 | 2.01 | 1.03714 |
| **Inventors** | 29 | 1 | 5 | 2 | 1.23576 |
| **Valid N (listwise)** | 29 | | | | |

**TABLE 7-6: IV Sample Assignee Details**

| Assignee | Type | No. of Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| PINCHEFSKY BARRY [US] | I | 1 | Not Applicable | | |
| MECHANICAL TECH INC [US] | C | 3 | | Mechanical Technology Incorporated (MTI) is engaged in the design, manufacture, and sale of test and measurement instruments and systems through its subsidiary MTI Instruments Incorporated. MTI Instrument's products use a comprehensive array of technologies to solve complex, real world applications in numerous industries including manufacturing, electronics, semiconductor, solar, commercial and military aviation, automotive and data storage. | USD 1857000 Revenue in 2017 |
| OLSEN JOHN H [US] | I | 1 | Not Applicable | | |
| CUMMINS POWER GENERATION INC [US] | C | 1 | 1919 | The Power Systems Segment is a global provider of high-speed high-horsepower engines and power generation equipment, including standby and prime power generator sets, alternators, switchgear and other components. Power Systems offers engines, power generation systems, components and services, and alternative-fuel electrical generators for use in residential standby, commercial industrial, mining, marine, oil and gas, defense, data centers, telecom and healthcare applications and industries, to name a few. | USD 17509 M Net sales in 2016 |
| MCQ ASSOCIATES INC [US]; KAB LAB INC [US] | C | 1 | 1992 | MCQ is a privately held company in Fredericksburg, VA and is a Single Location business. Categorized under Measuring/Controlling Devices (Unclassified) Manufacturers. The company produces low powered remote sensors that provide very high-end signal processing and network based communications architectures. They also have advanced sensor technology with custom solutions for a variety of government clients—achieving breakthroughs in digital imaging systems and acoustic, seismic, thermal, and magnetic sensor processing. | Not Available |
| KONOTCHICK, JOHN A | I | 1 | Not Applicable | | |
| CEFO NEVRES | I | 1 | Not Applicable | | |
| MURRAY LAWRENCE D | I | 1 | Not Applicable | | |
| WESTINGHOUSE AIR BRAKE TECHNOLOGIES CORPORATION | C | 1 | 1869 | Westinghouse Air Brake Technologies Corp., doing business as Wabtec Corp., provides technology-based equipment and services for the rail industry worldwide. The company operates in two segments, Freight Group and Transit Group. | USD 2.9B net sales in 2016 (Wabtec Corporation) |
| STIRLING TECHNOLOGY CO [US] | C | 1 | Information unavailable | | |
| SEIKI EPSON CORP [JP] | C | 1 | 1942 | Seiko Epson Corporation manufactures communications equipment, electronic devices, and precision products. The Company's products include printers, scanners, Liquid Crystal Projectors, semiconductors, quartz devices, and watches. | JYP 1024856 M in 2017 |
| NORTHROP GRUMMAN CORPORATION | C | 1 | 1939 | Northrop Grumman Corporation is an American global aerospace and defence technology company formed by Northrop's 1994 purchase of Grumman. Northrop Grumman is made up of three business sectors: Aerospace Systems, Mission Systems, and Technology Services. | USD 6.5 B in Q3 2017 |
| ENOCEAN GMBH [DE] | C | 1 | 2001 | EnOcean GmbH is the developer of the patented energy harvesting wireless technology marketed under the brands Dolphin and Easyfit. Headquartered in Oberhaching, near Munich, the company produces and markets self-powered wireless sensor solutions for batteryless applications in the Internet of Things, which are used for building and industrial automation, smart homes and LED lighting control. | Not Available |
| INCELEX LLC [US] | C | 1 | Information unavailable | | |
| PERPETUUM LTD [GB] | C | 5 | 2004 | Perpetuum Ltd. engineers, manufactures, and commercializes electromagnetic vibration harvesting micro generators. It offers battery-free vibration energy harvesters and wireless sensor nodes for passenger and freight applications; and industrial vibration energy harvesters and industrial wireless sensor nodes that are used for process monitoring and equipment condition-based monitoring in industrial environments. The company also provides wireless transmitters and programmable measurement nodes. It serves rail, oil and gas, | Not Available |

| Assignee | Type | No. of Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| | | | | chemicals, power generation, water and wastewater treatment, and process manufacturing industries. | |
| AISIN SEIKI [JP]; TOYODA CHUO KENKYUSHO KK [JP] | C | 1 | 1965 | Aisin is a Japanese corporation which develops and produces components and systems for the automotive industry. Aisin is a Fortune Global 500 company, ranked 442 on the 2015 rankings. Aisin Seiki was founded in 1949 and currently supplies engine, drivetrain, body and chassis, aftermarket, and other main automotive parts for various major OEMs. In addition to partaking in the automotive markets, Aisin also offers life and amenity products (e.g. furniture and sewing machines), energy systems, welfare products, and other products/services | JYP 45 B Capital 2017 |
| AQUA MAGNETICS INC [US] | C | 1 | | AMI's OSWEC (Ocean Swell Wave Energy Conversion) system is an innovative energy system that directly converts motion to electric power and poses no threat to the environment. It is an efficient, clean source of energy that uses no hydrocarbon fuel, hydraulic pumping units, or thermodynamics. | Not Available |
| INNOVATIVE TECH LICENSING LLC [US] | C | 1 | Information unavailable | | |
| UNIV MICHIGAN [US] | R | 1 | 1817 | The University of Michigan, is a public research university in Ann Arbor, Michigan. | |
| UNIV SOUTHAMPTON [GB] | R | 2 | 1952 | The University of Southampton is a public research university located in Southampton, England. | |
| SUMIDA CORP [JP] | C | 1 | 1956 | Sumida Corporation manufactures coils and related parts for electronic equipment. The Company's products are used for audio/video, office automation, data processing, cellular phones, and automobiles. Sumida Corporation has its subsidiaries in Hong Kong, Malaysia, Taiwan, the US, and China | 8,143 M JPY Capital 2017 |
| SOUTHWEST RES INST [US] | R | 1 | 1947 | Southwest Research Institute (SwRI), headquartered in San Antonio, Texas, is one of the oldest and largest independent, non-profit, applied research and development (R&D) organizations in the United States. | |

*C=Corporate*

*I=Individual*

*R=Research Organization*

*M=Million*

*B=Billion*

*USD=US Dollars*

*JPY=Japanese Yen*

**TABLE 7-7: PZ Sector Sample Details**

| Patent Number | Title | Filing Date | Grant Date | Assignee | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US4814660 | Piezoelectric motor with multilayer piezoelectric elements | 11/02/1988 | 21/03/1989 | NEC CORP [JP] | 32 | 11 | 1 |
| US4831306 | Piezoelectric motor having a pivotally mounted annular shaped housing | 4/05/1988 | 16/05/1989 | MICRO PULSE RESEARCH AND DEV [US] | 17 | 4 | 3 |
| US4833358 | Vibration wave motor | 14/12/1987 | 23/05/1989 | CANON KK [JP] | 55 | 21 | 3 |
| US4833359 | Driving apparatus for ultrasonic motor | 12/01/1988 | 23/05/1989 | MATSUSHITA ELECTRIC IND CO LTD [JP] | 12 | 9 | 3 |
| US4849668 | Embedded piezoelectric structure and control | 19/05/1987 | 18/07/1989 | MASSACHUSETTS INST TECHNOLOGY [US] | 175 | 10 | 7 |
| US4853578 | Driving apparatus for ultrasonic motor | 5/01/1988 | 1/08/1989 | MATSUSHITA ELECTRIC IND CO LTD [JP] | 11 | 12 | 2 |
| US4853580 | Piezoelectric pulse generator | 5/08/1988 | 1/08/1989 | TEKTRONIX INC [US] + | 19 | 11 | 1 |
| US4868446 | Piezoelectric revolving resonator and ultrasonic motor | 28/03/1988 | 19/09/1989 | HITACHI MAXELL [JP] | 25 | 12 | 5 |
| US4868447 | Piezoelectric polymer laminates for torsional and bending modal control | 11/09/1987 | 19/09/1989 | CORNELL RES FOUNDATION INC [US | 86 | 20 | 1 |
| US4871939 | Piezoelectric motor | 21/12/1987 | 3/10/1989 | EMHART IND [US] | 20 | 8 | 2 |
| US4876776 | Method of making piezoelectric composites | 11/02/1988 | 31/10/1989 | PLESSEY OVERSEAS [GB] | 29 | 5 | 2 |
| US4885498 | Stacked type piezoelectric actuator | 18/06/1986 | 5/12/1989 | NGK SPARK PLUG CO [JP] | 30 | 8 | 1 |
| US4885499 | Ultrasonic driven type motor | 10/02/1989 | 5/12/1989 | NGK SPARK PLUG CO [JP] | 9 | 18 | 3 |
| US4888514 | Driving apparatus for ultrasonic motor | 13/10/1988 | 19/12/1989 | MATSUSHITA ELECTRIC IND CO LTD [JP] | 43 | 9 | 9 |
| US4893046 | Ultrasonic driving device | 8/09/1988 | 9/01/1990 | HONDA ELECTRONIC [JP] | 9 | 3 | 2 |
| US4894579 | Apparatus for effecting fine movement by impact force produced by | 23/05/1988 | 16/01/1990 | JAPAN RES DEV CORP [JP] | 55 | 5 | 4 |

| Patent Number | Title | Filing Date | Grant Date | Assignee | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| | piezoelectric or electrostrictive element | | | | | | |
| US4902926 | Piezoelectric measuring element | 10/11/1988 | 20/02/1990 | AVL VERBRENNUNGSKRAFT MESSTECH [AT] | 11 | 9 | 2 |
| US4912351 | Piezoelectric motor | 22/09/1988 | 27/03/1990 | HITACHI LTD [JP] | 29 | 17 | 4 |
| US4914338 | Vibration wave motor | 17/09/1989 | 3/04/1990 | CANON KK [JP] | 7 | 7 | 1 |
| US4929859 | Piezoelectric actuator having parallel arrangement of a single piezoelectric element and a pair of displacement magnification arms | 12/12/1988 | 29/05/1990 | TOYOTA MOTOR CO LTD [JP] | 11 | 18 | 2 |
| US4933591 | Double saggital pull stroke amplifier | 6/12/1988 | 12/06/1990 | FORD AEROSPACE CORP [US] | 16 | 27 | 2 |
| US4943752 | Piezoelectric incandescent lamp test device | 8/09/1988 | 24/06/1990 | TODD PHILIP A [US]; WALKER BOBBY R [US] | 19 | 14 | 2 |
| US4944891 | Easily poled 0-3 piezoelectric composites for transducer applications | 6/03/1987 | 31/07/1990 | HOECHST CELANESE CORP [US] | 10 | 7 | 2 |
| US4947076 | Piezo electric motor | 16/12/1988 | 7/08/1990 | HITACHI MAXELL [JP] | 18 | 9 | 2 |
| US4952834 | Circuitry for driving ultrasonic motor | 10/03/1989 | 28/08/1990 | OLYMPUS OPTICAL CO [JP] | 61 | 5 | 2 |
| US4952835 | Double saggital push stroke amplifier | 27/12/1988 | 28/08/1990 | FORD AEROSPACE CORP [US] | 22 | 8 | 7 |
| US4952836 | Piezoelectrostatic generator | 27/04/1989 | 28/09/1990 | NASA [US] | 15 | 10 | 1 |
| US4954742 | Vibratory-wave motor device | 30/12/1988 | 4/09/1990 | CANON KK [JP] | 24 | 8 | 2 |
| US4958100 | Actuated truss system | 22/02/1989 | 18/09/1990 | MASSACHUSETTS INST TECHNOLOGY [US] | 57 | 14 | 7 |
| US4959580 | Piezoelectric motor | 26/02/1987 | 25/09/1990 | KI POLT I [SU] | 49 | 9 | 1 |
| US4968914 | High resolution electromechanical translation device | 24/03/1989 | 6/11/1990 | QUANSCAN INC [US] | 23 | 7 | 1 |
| US4975615 | Piezoelectric transducer | 8/06/1989 | 4/12/1990 | ATLANTIC RICHFIELD CO [US] | 13 | 10 | 1 |
| US4980597 | Ultrasonic motor with vibration suppressor | 24/04/1990 | 25/12/1990 | BROTHER IND LTD [JP] | 13 | 4 | 1 |

| Patent Number | Title | Filing Date | Grant Date | Assignee | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| US4980599 | | 12/02/1990 | 25/12/1990 | AISIN SEIKI [JP] | 10 | 8 | 1 |
| US4983874 | Vibrator and ultrasonic motor employing the same | 3/07/1989 | 8/01/1991 | BROTHER IND LTD [JP] | 12 | 7 | 3 |
| US4994703 | Piezoelectric element of laminate type | 7/07/1989 | 19/02/1991 | MITSUBISHI CHEM IND [JP] | 15 | 3 | 4 |
| US5004945 | Piezoelectric type actuator | 22/09/1989 | 2/04/1991 | NIPPON DENSO CO [JP] | 41 | 11 | 5 |
| US5008581 | Piezoelectric revolving resonator and single-phase ultrasonic motor | 10/04/1989 | 16/04/1991 | HITACHI MAXELL [JP]; DEMIX TECHNOLOGY INC [JP] | 23 | 11 | 6 |
| US5021700 | Driving apparatus for ultrasonic motor | 21/09/1989 | 4/06/1991 | MATSUSHITA ELECTRIC IND CO LTD [JP] | 31 | 12 | 6 |
| US5027028 | Piezoelectric motor | 29/08/1989 | 25/06/1991 | SKIPPER JOHN D [US] | 28 | 14 | 1 |
| US5032754 | Piezoelectric transducer for an ultrasonic motor | 19/03/1990 | 16/07/1991 | BROTHER IND LTD [JP] | 5 | 13 | 1 |
| US5034649 | Piezoelectric actuator | 28/09/1990 | 23/07/1991 | MITSUBISHI CHEM IND | 23 | 13 | 6 |
| US5036241 | Piezoelectric laminate and method of manufacture | 3/02/1989 | 30/07/1991 | XAAR LTD [GB] | 14 | 11 | 3 |
| US5036245 | Ultrasonic linear motor | 13/11/1989 | 30/07/1991 | ALPS ELECTRIC CO LTD [JP] | 32 | 5 | 1 |
| US5039899 | Piezoelectric transducer | 27/02/1990 | 13/08/1991 | BROTHER IND LTD [JP] | 52 | 13 | 1 |
| US5039901 | Electric power source through steam transition | 22/06/1990 | 13/08/1991 | NEWBOULD JOHN M [US] | 9 | 8 | 1 |
| US5047162 | Piezoelectric composite materials and method of making | 26/06/1989 | 10/09/1991 | MARTIN MARIETTA CORP [US] | 9 | 3 | 6 |
| US5049774 | Vibratory motor | 31/10/1989 | 17/09/1991 | AISIN SEIKI [JP] | 7 | 9 | 1 |
| US5051647 | Ultrasonic motor | 5/07/1990 | 24/09/1991 | NEC CORP [JP] | 29 | 6 | 4 |
| US5055732 | Ultrasonic motor | 21/12/1990 | 8/10/1991 | AISIN SEIKI [JP] | 9 | 6 | 1 |
| US5056201 | Method of making a travelling-wave motor | 13/07/1990 | 15/10/1991 | SEIKO INSTR INC [JP] | 13 | 4 | 1 |
| US5065067 | Piezoelectric circuit | 12/05/1989 | 12/11/1991 | TODD PHILIP A [US]; WALKER BOBBY R [US] | 42 | 21 | 8 |
| US5073739 | Vibration-coupling type ultrasonic actuator and method | 27/02/1991 | 17/12/1991 | NISCA CORP [JP] | 26 | 6 | 3 |

| Patent Number | Title | Filing Date | Grant Date | Assignee | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|---|
| | for operating the same | | | | | | |

**TABLE 7-8: PZ Sample Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| **Citations** | 53 | 5 | 175 | 27 | 26.74 |
| **References** | 53 | 3 | 27 | 10 | 5.13 |
| **Family Size** | 53 | 1 | 9 | 3 | 2.17 |
| **Claims** | 53 | 2 | 54 | 11 | 10.02 |
| **Processing Time** | 53 | 0.5 | 3.6 | 1.59 | 0.63 |
| **Inventors** | 53 | 1 | 7 | 2 | 1.25 |
| **Valid N (listwise)** | 53 | | | | |

## TABLE 7-9: PZ Sample Assignee Details

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| BROTHER IND LTD [JP] | C | 4 | 1908 | BROTHER INDUSTRIES, LTD. is a Japan-based company engaged in the manufacture and sale of office equipment and supplies. The Company operates in six business segments; Printing and Solutions, Personal and Home, Machinery and Solution, Network and Contents, Industrial component and Others segment. | USD 5761M Revenue |
| MATSUSHITA ELECTRIC IND CO LTD [JP] | C | 4 | 1918 | Panasonic Corporation, formerly known as Matsushita Electric Industrial Co., Ltd, is a Japanese multinational electronics corporation headquartered in Kadoma, Osaka, Japan. In addition to electronics, it offers non-electronic products and services such as home renovation services. Panasonic is the world's fourth-largest television manufacturer by 2012 market share. | USD 34.8B Market Cap in 2017 |
| AISIN SEIKI [JP] | C | 3 | 1965 | Aisin Seiki Co., Ltd. engages in the manufacture and sale of automotive parts. It operates through the following segments: Aisin Seiki Group, Aisin Takaoka Group, Aisin AW Group, Advics Group, and Others. | JPY 45B Market Cap in 2017 |
| CANON KK [JP] | C | 3 | 1937 | Canon Inc. is a Japanese multinational corporation specialized in the manufacture of imaging and optical products, including cameras, camcorders, photocopiers, steppers, computer printers and medical equipment. It is headquartered in Ōta, Tokyo, Japan. | USD 1299 M net income in 2017 |
| FORD AEROSPACE CORP [US] | C | 2 | 1956 | Ford Aerospace (1956−1990) was the aerospace and defence division of Ford Motor Company and developed technology in surface-to-air missile and air-to-air missile and bomb-targeting systems. It was based in Newport Beach, Orange County, California. In 1990 Ford Aerospace was sold to Loral Corporation. | Not Available |
| HITACHI MAXELL [JP] | C | 2 | 1960 | Hitachi Maxell, Ltd., commonly known as Maxell, is a Japanese company that manufactures consumer electronics. The company's notable products are batteries—the company's name is a contraction of "maximum capacity dry cell"—wireless charging solutions, storage devices, computer tapes, professional broadcast tapes and functional materials. In the past, the company manufactured recording media, including audio cassettes and blank VHS tapes, and recordable optical discs including CD-R/RW and DVD±RW. | JPY 5 B Capital in 2017 |
| MASSACHUSETTS INST TECHNOLOGY [US] | R | 2 | 1861 | MIT is often ranked as one of the world's most prestigious universities. The Institute is traditionally known for its research and education in the physical sciences and engineering, but more recently in biology, economics, linguistics, and management as well. | Not Available |
| MITSUBISHI CHEM IND [JP] | C | 2 | 1934 | Mitsubishi Chemical Corporation manufactures chemical products. The Company develops, produces, and sells performance products, health care products, industrial materials, and other chemicals. Mitsubishi Chemical provides their products for construction, medical, energy, and petrochemical fields. | JPY 2417.9 B Sales |
| NEC CORP [JP] | C | 2 | 1899 | NEC Corporation is a Japanese multinational company and is a provider of information technology (IT) services and products, | JPY 397.2 B in 2017 |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| NGK SPARK PLUG CO [JP] | C | 2 | 1936 | NGK SPARK PLUG Co., Ltd. manufactures and markets spark plugs for automobiles, motorcycles, agricultural machinery, ships, and aircrafts. The Company also makes ceramic products for semiconductor and telecommunication equipment. NGK Spark Plug markets its products under the NGK and NTK brand names and has subsidiaries in the US, Canada, France, Germany, and South Korea. | JPY 47869 M in 2017 |
| TODD PHILIP A [US]; WALKER BOBBY R [US] | I | 2 | Not Applicable | | |
| ALPS ELECTRIC CO LTD [JP] | C | 1 | 1948 | Alps Electric Co., Ltd. is a Japanese multinational corporation, headquartered in Tokyo, Japan, producing electronic devices, including switches, potentiometers, sensors, encoders and touchpads. The company was established in 1948 as Kataoka Electric Co., Ltd. and changed its name to Alps Electric Co., Ltd. in December 1964. | JPY 753.26 B Net Sales in 2017 |
| ATLANTIC RICHFIELD CO [US] | C | 1 | 1966 | The Atlantic Richfield Company was created in 1966 by the merger of Richfield Oil Corporation and Atlantic Refining Company. | USD10.3 B sales in 1998 |
| AVL VERBRENNUNGSKRAFT MESSTECH [AT] | C | 1 | 1946 | AVL develops and improves all kinds of powertrain systems and is a competent partner to the engine and automotive industry. In addition AVL develops and markets the simulation methods which are necessary for the development work. | Euro 1.4 B turnover in 2016 |
| CORNELL RES FOUNDATION INC [US | R | 1 | | The organization's mission is to foster inventiveness at Cornell, protect Cornell's intellectual property interests and manage those interests for the benefit of Cornell, its inventors and the public. | Not Available |
| EMHART IND [US] | C | 1 | | Not Available | Not Available |
| HITACHI LTD [JP] | C | 1 | 1910 | Hitachi, Ltd. is a Japanese multinational conglomerate company headquartered in Chiyoda, Tokyo, Japan. It is the parent company of the Hitachi Group (Hitachi Gurūpu) and forms part of the DKB Group of companies. Hitachi is a highly diversified company that operates eleven business segments: Information & Telecommunication Systems, Social Infrastructure, High Functional Materials & Components, Financial Services, Power Systems, Electronic Systems & Equipment, Automotive Systems, Railway & Urban Systems, Digital Media & Consumer Products, Construction Machinery and Other Components & Systems. | JPY 9.16 T Revenue in 2017 |
| HITACHI MAXELL [JP]; DEMIX TECHNOLOGY INC [JP] | C | 1 | | Joint Venture | |
| HOECHST CELANESE CORP [US] | C | 1 | 1918 | Celanese Corporation, also known as Hoechst Celanese, is a Fortune 500 global technology and specialty materials company with its headquarters in Irving, Texas, United States. The company is a leading producer of acetyl products, which are intermediate chemicals for nearly all major industries, and is the world's largest producer of vinyl | $1.28 Earnings Before Interest and Tax (EBIT) |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| | | | | acetate monomer (VAM). | USD in 2016 |
| HONDA ELECTRONIC [JP] | C | 1 | 1956 | The Company's line of business includes the manufacturing of electrical equipment and supplies. | JPY 100,000,000 Capital in 2010 |
| JAPAN RES DEV CORP [JP] | R | 1 | 1961 | JRDC was organized in July 1961 with missions to reduce the country's dependence on overseas technologies, to select and support outstanding research at universities and public research institutions in Japan, and to promote technology transfer of such research output to the private sector. | Not Available |
| KI POLT I [SU] | R | 1 | 1898 | The National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute" is a major university in Kiev, Ukraine. In January 2012 Webometrics Ranking KPI made it into top 1,000 – taking 957th place out of 20,300 universities, 510th (February 2013). | Not Available |
| MARTIN MARIETTA CORP [US] | C | 1 | 1961 | The Martin Marietta Corporation was an American company founded in 1961 through the merger of Glenn L. Martin Company and American Marietta Corporation. The combined company became a leader in chemicals, aerospace, and electronics. In 1995, it merged with Lockheed Corporation to form Lockheed Martin. | Not Available |
| MICRO PULSE RESEARCH AND DEV [US] | | 1 | | Not Available | Not Available |
| NASA [US] | R | 1 | 1958 | The National Aeronautics and Space Administration (NASA) is an independent agency of the executive branch of the United States federal government responsible for the civilian space program, as well as aeronautics and aerospace research. | Not Available |
| NEWBOULD JOHN M [US] | I | 1 | Not Applicable | | |
| NIPPON DENSO CO [JP] | C | 1 | 1949 | DENSO is a leading supplier of advanced automotive technology, systems and components for major automakers. Currently, Denso ranks the second largest auto parts supplier in the world. | Revenue JPY 4527B in 2017 |
| NISCA CORP [JP] | C | 1 | 1960 | The Company's principal activity is manufactures office automation equipment, information systems, optical devices, and other electronic components. The company's products include card printer; office automation products, including automatic document feeder, reversing auto document feeder, bin sorter, auto duplex device, and colour copy machine; information systems' products, such as colour card printing system, multimedia camera, auto document feeder for scanner, receipt and journal printer, automatic teller machine, and plotter; optomechatronic products, including auto iris, ring iris, lens unit with auto iris, auto focus unit, programmable shatter, shutter for zoom camera, and shutter with auto focus; and motors and other electronic products. Nisca also provides pan-tilt cameras. The company was founded as Nihon Seimitsu Kogyo K.K. in 1960 by Nihon Kohden and changed its name to Nisca Corporation in 1990. On 25 June 2008, | Not Available |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| | | | | become wholly-owned subsidiary of Canon FineTech Inc and delisted from stock exchange. | |
| OLYMPUS OPTICAL CO [JP] | C | 1 | 1919 | Olympus Optical Co., Ltd. is a prestigious manufacturer of a wide array of high-tech medical and healthcare, imaging and information, and industrial equipment. The company is renowned for SLR and Digital cameras, and other photography and optical equipment, but its name is equally famous for products like medical endoscopes, microscopes, clinical analysers, reagents, microcassette and IC recorders, magneto-optical drives, printers, bar-code scanners, industrial endoscopes and motors | JPY 748B in 2017 |
| PLESSEY OVERSEAS [GB] | C | 1 | 1917 | The Plessey Company plc was a British-based international electronics, defence and telecommunications company. It originated in 1917, growing and diversifying into electronics. It expanded after the Second World War by acquisition of companies and formed overseas companies. In 1989, it was taken over by a consortium formed by GEC and Siemens, which split the assets of the Plessey group. | Not Available |
| QUANSCAN INC [US] | C | 1 | | According to SBIR's (small business innovation research program www.sbir.gov) website, Quanscan is registered in Pasadena CA as a small business with 6 employees | |
| SEIKO INSTR INC [JP] | C | 1 | 1937 | Seiko Instruments Inc., or SII, is a Japanese company, which develops and commercializes semiconductor, micromechatronics, and precision timepiece technology. It is one of three core companies of the Seiko Group. The company manufactures and sells electronic components (semiconductors, crystal oscillators, micromechatronics devices, thermal printer, coin battery, liquid crystal displays), precision parts, watches, analysis and measurement instruments, machine tools, printers, network items, information systems and services, IC dictionaries, etc. | JPY 9756M in 2017 |
| SKIPPER JOHN D [US] | I | 1 | Not Applicable | | |
| TEKTRONIX INC [US] | C | 1 | 1946 | Tektronix, Inc. manufactures and sells test, measurement, and monitoring solutions to companies involved in the semiconductor, computer, and networking industries. The Company's products are used to assist in the design, building, deployment, and management of global communications networks and Internet technologies. On November 21, 2007, Tektronix was acquired by Danaher Corporation for $2.85 billion | Not Available |
| TOYOTA MOTOR CO LTD [JP] | C | 1 | 1937 | Toyota Motor Corporation is a Japanese multinational automotive manufacturer headquartered in Toyota, Aichi, Japan. Toyota is the world's market leader in sales of hybrid electric vehicles, and one of the largest companies to encourage the mass-market adoption of hybrid vehicles across the globe. | JPY 635B Capital in 2016 |
| XAAR LTD [GB] | C | 1 | 1990 | Xaar is an independent manufacturer of piezo-based drop-on-demand inkjet technologies. This company was formed in Cambridge UK, to commercially develop a new digital inkjet technology arising out of work done by Cambridge Consultants Ltd. | GBP 96.2M revenue in 2016 |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|

*C=Corporate*

*I=Individual*

*R=Research Organization*

*M=Million*

*B=Billion*

*USD=US Dollars*

*JPY=Japanese Yen*

*GBP = Great Britain Pound*

**TABLE 7-10: CNT Sector Sample Details**

| Patent No. | Filing Date | Grant Date | Assignee | Forward Citations | References | INPADOC Family |
|---|---|---|---|---|---|---|
| US6013207 | 5/11/1997 | 1/11/2000 | TAKAHASHI, MINORU, ; HARADA, RYOJI | 1 | 4 | 3 |
| US6045769 | 8/12/1997 | 4/04/2000 | NANOGRAM CORP [US] | 27 | 13 | 4 |
| US6149775 | 9/03/1999 | 21/11/2000 | FUTABA DENSHI KOGYO KK [JP | 37 | 2 | 4 |
| US6157043 | 22/12/1997 | 5/12/2000 | NEC CORP [JP] | 24 | 2 | 2 |
| US6183714 | 26/07/1996 | 6/02/2001 | RICE UNIVERSITY | 279 | 30 | 11 |
| US6187823 | 29/09/1999 | 13/02/2001 | UNIV KENTUCKY RES FOUND [US] | 171 | 9 | 5 |
| US6203864 | 8/06/1999 | 20/03/2001 | NEC CORP [US] | 112 | 2 | 6 |
| US6228498 | 18/03/1999 | 8/05/2001 | AGENCY IND SCIENCE TECHN [US] | 4 | 4 | 2 |
| US6251522 | 20/03/1998 | 26/06/2001 | JAPAN SCIENCE & TECH CORP [US]; TOSHIBA KK [US] | 20 | 5 | 6 |
| US6261532 | 23/03/1999 | 17/07/2001 | RES INST INNOVATIVE TECH EARTH [US]; SHIMADZU CORP [US] | 19 | 4 | 6 |
| US6283812 | 25/01/1999 | 4/09/2001 | AGERE SYST GUARDIAN CORP [US] | 208 | 20 | 6 |
| US6303094 | 20/11/1998 | 16/10/2001 | JAPAN FINE CERAMICS CT [US] | 67 | 6 | 4 |
| US6334939 | 15/06/2000 | 1/01/2002 | UNIV NORTH CAROLINA [US] | 119 | 4 | 8 |
| US6346023 | 24/08/1999 | 12/02/2002 | FUTABA DENSHI KOGYO KK [JP] | 32 | 3 | 3 |
| US6346189 | 14/08/1998 | 12/02/2002 | UNIV LELAND STANFORD JUNIOR [US] | 266 | 6 | 9 |
| US6350488 | 2/06/2000 | 26/02/2002 | ILJIN NANOTECH CO LTD | 170 | 6 | 5 |
| US6355225 | 5/10/1999 | 12/03/2002 | UNIV WM MARSH RICE [US]; TDA RESEARCH INC [US] | 12 | 10 | 5 |
| US6358375 | 3/12/1999 | 19/03/2002 | ARMINES [FR] | 33 | 9 | 13 |
| US6386468 | 29/11/1999 | 20/11/1999 | CERAMOPTEC IND INC [US] | 7 | 3 | 3 |
| US6401526 | 10/12/1999 | 11/06/2002 | UNIV LELAND STANFORD JUNIOR [US] | 158 | 14 | 2 |
| US6426134 | 29/06/1999 | 20/07/2002 | DU PONT [US] | 227 | 12 | 1 |
| US6451175 | 15/08/2000 | 17/09/2002 | WISCONSIN ALUMNI RES FOUND [US] | 46 | 23 | 1 |
| US6455021 | 20/07/1999 | 24/09/2002 | SHOWA DENKO KK | 25 | 5 | 2 |
| US6479028 | 3/04/2000 | 12/11/2002 | UNIV CALIFORNIA [US] | 67 | 19 | 1 |
| US6495258 | 20/09/2000 | 17/12/2002 | UNIV AUBURN [US | 203 | 4 | 1 |

**TABLE 7-11: CNT Sample Descriptive Statistics**

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| **Citations** | 25 | 1 | 279 | 93 | 89.9 |
| **References** | 25 | 2 | 30 | 9 | 7.4 |
| **Family Size** | 25 | 1 | 13 | 5 | 3.2 |
| **Claims** | 25 | 3 | 48 | 16 | 11.4 |
| **Processing Time** | 25 | 0 | 4.5 | 2.42 | 0.9 |
| **Inventors** | 25 | 1 | 7 | 3 | 1.5 |
| **Valid N (listwise)** | 25 | | | | |

**TABLE 7-12: CNT Sample Assignee Details**

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| AGENCY IND SCIENCE TECHN [JP] | R | 1 | | | Not Applicable |
| AGERE SYST GUARDIAN CORP [US] | C | 1 | 2000 | Spun out of Lucent Technologies in 2002. As of December 3, 2006, Agere Systems Guardian Corporation was merged into LSI Corporation. | Not Available |
| ARMINES [FR] | R | 1 | 1967 | ARMINES is a private non-profit research and technological organisation (RTO) funded in 1967 at the instigation of its partner engineering schools, the Écoles des Mines network. | |
| CERAMOPTEC IND INC [US] | C | 1 | - | CeramOptec is a world leader in the production of specialty optical fiber and fiber optic-based products for industrial, scientific, medical, and dental applications. CeramOptec manufactures high quality specialty optical fiber, bundles, and spectroscopic accessories with unmatched delivery times.<br><br>CeramOptec produces stock and custom silica, silica, plastic-clad silica, and hard polymer-clad silica optical fibers; fused capillary tubing; DPSS lasers; diode modules; and low loss bundles and assemblies for UV, VIS, and IR transmission, medical laser delivery, sensors, plasma fusion, and spectroscopy. The company seems to have moved operations to Germany. No additional details are available. | Private Company |
| DU PONT [US] | C | 1 | 1802 | E. I. du Pont de Nemours and Company, commonly referred to as DuPont, is an American conglomerate. In the 20th century, DuPont developed many polymers such as Vespel, neoprene, nylon, Corian, Teflon, Mylar, Kapton, Kevlar, Zemdrain, M5 fiber, Nomex, Tyvek, Sorona, Corfam, and Lycra. DuPont developed Freon (chlorofluorocarbons) for the refrigerant industry, and later more environmentally friendly refrigerants. It also developed synthetic pigments and paints including ChromaFlair. | USD 24.5B Revenue in 2016 |
| FUTABA DENSHI KOGYO KK [JP] | C | 2 | 1948 | FUTABA CORPORATION was established in 1948 as a manufacturer and seller of receiver vacuum tubes.<br>Utilizing vacuum tube technology, Futaba began manufacturing vacuum fluorescent displays. In 1962, Futaba began producing radio control equipment as well as press die set components, establishing what still remains as two of the company's primary divisions.<br>This was followed by the development of mold base components and the more recent addition of VFD modules to complete the line-up of Futaba's major products. | JPY 69830 M Sales 2016 |
| ILJIN NANOTECH CO LTD | C | 1 | - | Not Available | |
| JAPAN FINE | R | 1 | 1985 | Established in 1985. R&D-based organization for | Not |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| CERAMICS CT [US] | | | | standardization, quality improvement and expansion of uses and applications of advanced ceramics, engineering ceramics and electronic ceramics. Offers contract-basis tests and research, international exchanges, public relations and promotional activities. | Applicable |
| JAPAN SCIENCE & TECH CORP [US]; TOSHIBA KK [US] | R-C | 1 | - | Joint Venture | |
| NANOGRAM CORP [US] | C | 1 | 1996 | NanoGram Corporation provides customized application-specific nanotechnology solutions through a manufacturing platform to its partners. The company manufactures and licenses materials process technology, electrodes, silicon-on-plastic prototypes, tools, and solutions that enable the manufacture of nanoscale compositions for optical, electronic, imaging, biomedical, solar cells, and energy applications. Its licensing package includes materials production process, surface modification and dispersion technologies, process transfer expertise, and ongoing support. | Private Company |
| NEC CORP [JP] | C | 2 | 1899 | On 17 July 1899, Nippon Electric Company, Limited (renamed NEC Corporation, effective April, 1983, both expressed as NEC hereafter) Japan's first joint venture with foreign capital, was established by Kunihiko Iwadare in association with the U.S. firm Western Electric Company (presently Alcatel-Lucent). The basic aim of the new company, expressed in the slogan "Better Products, Better Service," was to carry out the promise to provide its customers with world-class products and dependable follow-up service. | JPY 397.2B in 2017 |
| RES INST INNOVATIVE TECH EARTH; SHIMADZU CORP | R-C | 1 | - | Joint Venture | |
| RICE UNIVERSITY | R | 1 | 1912 | Rice University, officially William Marsh Rice University, is a private research university located on a 295-acre campus in Houston, Texas, United States. The university is situated near the Houston Museum District and is adjacent to the Texas Medical Center. Rice is generally considered the top university and the most selective institution of higher education in the state of Texas. | Not Applicable |
| SHOWA DENKO KK | C | 1 | 1939 | Showa Denko K.K. (SDK) manufactures chemical products and industrial materials. SDK's products serve a wide array of fields ranging from heavy industry to the electronic and computer industries. The company is divided in five business sectors: petrochemicals (olefins, organic chemicals, plastic products), aluminum (aluminum cans, sheets, ingots, foils), electronics (semiconductors, ceramic materials, hard disks), chemicals (industrial gases, ammonia, agrochemicals), and inorganic | JYP 671.2 B Net Sales in 2016 |

| Assignee | Type | Patents | Established | Details | Financials |
|---|---|---|---|---|---|
| | | | | materials (ceramics, graphite electrodes). | |
| TAKAHASHI, MINORU, ; HARADA, RYOJI | I | 1 | - | Not Applicable | |
| UNIV AUBURN [US | R | 1 | 1856 | Auburn University (AU or Auburn) is a public research university in Auburn, Alabama, United States. | Not Applicable |
| UNIV CALIFORNIA [US] | R | 1 | 1868 | The University of California (UC) is a public university system in the U.S. state of California. | Not Applicable |
| UNIV KENTUCKY RES FOUND [US] | R | 1 | 1945 | The University of Kentucky Research Foundation (UKRF), a not-for-profit Kentucky corporation, was established in 1945 to receive, invest, and expend funds to promote and implement scientific, educational, and developmental activities at UK. UKRF serves as the university's agent in the receipt of all external grants and contracts, intellectual property income and other designated income; oversees the protection, development, and commercialization of intellectual properties; and manages special cooperative agreements. | Not Applicable |
| UNIV LELAND STANFORD JUNIOR [US] | R | 2 | 1891 | Stanford University (officially Leland Stanford Junior University) is a private research university in Stanford, California, | Not Applicable |
| UNIV NORTH CAROLINA [US] | R | 1 | 1972 | The University of North Carolina is a multi-campus public university system composed of all 16 of North Carolina's public universities, as well as the NC School of Science and Mathematics, the nation's first public residential high school for gifted students | Not Applicable |
| UNIV WM MARSH RICE [US]; TDA RESEARCH INC [US] | R-C | 1 | - | Joint Venture | |
| WISCONSIN ALUMNI RES FOUND [US] | R | 1 | 1925 | To support scientific research within the UW–Madison community by providing financial support, actively managing assets, and moving innovations to the marketplace for a financial return and global impact | Not Applicable |

*C=Corporate*

*I=Individual*

*R=Research Organization*

*R-C= Joint venture between research organization and corporate body*

*M=Million*

*B=Billion*

*USD=US Dollars*

*JPY=Japanese Yen*

# 8 RESULTS AND DISCUSSION

## 8.1 Introduction

In this chapter I discuss the results of the study. I start the chapter with observations on the knowledge structure of the inventions. I then replicate the methodology of a study from the literature to show that an analysis based on first-level patent indicators does not convey the full picture of patent value. I then discuss the results on KA followed by STRUCTURAL ROBUSTNESS. Finally, I build a model to predict the technical value based on both KA and STRUCTURAL ROBUSTNESS.

## 8.2 Knowledge Structure

Descriptive statistics of the sample set are given in TABLE 8-1. TFP samples display the largest knowledge structure with a mean of 429 patents in the knowledge network. An average KA of 0.18 (*SD=0.10*) is observed in these samples. The knowledge networks span over 12 generations and provide an observation period of over 100 years. The samples of IV sector have a mean KA of 0.78 *(SD = 0.36)*. These patents have an average of 10 generations of backward citations with the earliest patent dating back to 1903. This provided an observation period of over 100 years for each invention. On an average, the knowledge structure of each sample patent in this sector has a network of 62 patents. Thus, the initial 29 patents of IV sector drew their knowledge from over 1200 patents in their knowledge structure. Inventions in PZ sector have an average of 96 patents in their knowledge structure over 9 generations. These 53 inventions drew their knowledge from over 866 inventions. Patents in this sector displayed an average KA of 0.06 *(SD = 0.03)*. The earliest patent in this dataset dates back to 1926. This gives an observation period of 65 years for this sector. The samples from CNT sector displayed an average KA of 0.11 *(SD = 0.07).* Though the patenting activity started late in this sector, an average of 238 patents were found in the knowledge structure of the inventions. In this research, the earliest patent cited in the CNT sector, was published in 1915 giving an observation period of 100 years. The distribution of PV and KA of the samples is given in Figure 8-1and Figure 8-2 respectively.

*In conclusion, this research assesses the knowledge structure of 152 inventions and evaluates the direct and indirect influence of over 4817 knowledge elements on the technical value of these inventions.*

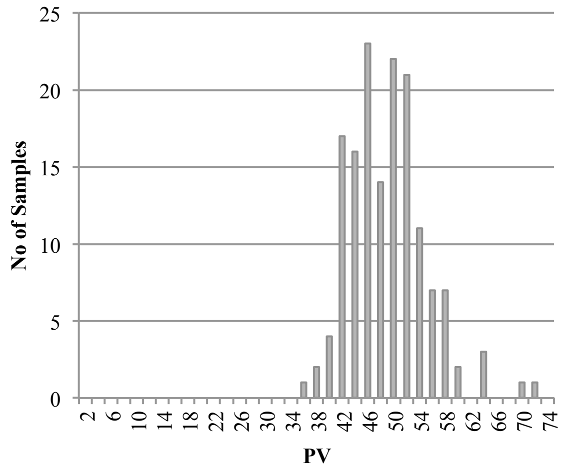



**Figure 8-1: Distribution of Patent Value in the sample set**

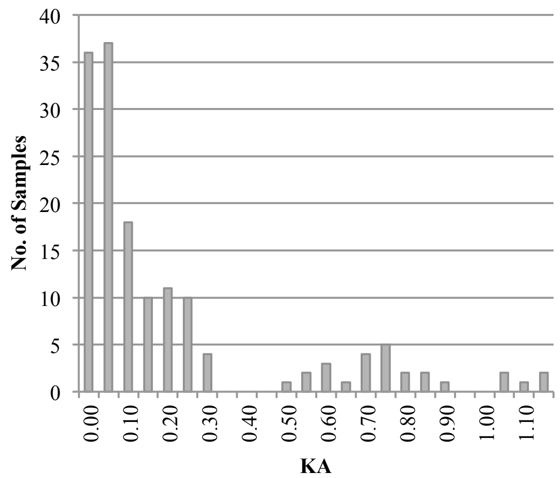



**Figure 8-2: Distribution of KA in the sample set**

**TABLE 8-1: Descriptive statistics of the sample sets.**

| | | KA | PV | Knowledge Elements | Generations | RC | NC | ASPL | Valid N (listwise) |
|---|---|---|---|---|---|---|---|---|---|
| | Min | 0.00 | 42.54 | 1.00 | 1.00 | 10.49 | 2.17 | 1.00 | 45.00 |
| | Max | 0.33 | 65.38 | 897.00 | 17.00 | 100.00 | 66.59 | 2.25 | |
| | Mean | 0.18 | 50.08 | 429.22 | 12.47 | 40.23 | 27.36 | 1.80 | |
| TFP | Std. Dev | 0.10 | 5.62 | 243.16 | 3.92 | 17.00 | 14.94 | 0.26 | |
| | Min | 0.01 | 41.47 | 3.00 | 1.00 | 13.61 | 4.41 | 1 | 29.00 |
| | Max | 1.66 | 70.18 | 185.00 | 18.00 | 100 | 75 | 1.89 | |
| | Mean | 0.78 | 50.00 | 62.00 | 10.00 | 38.17 | 29.64 | 1.59 | |
| IV | Std. Dev | 0.36 | 6.51 | 38.19 | 3.66 | 17.143 | 20.32 | 0.184 | |
| | Min | 0.01 | 37.90 | 13.00 | 4.00 | 9.26 | 3.23 | 1.24 | 53.00 |
| | Max | 0.11 | 72.58 | 204.00 | 13.00 | 63.31 | 61.54 | 1.77 | |
| PZ | Mean | 0.06 | 50.06 | 96.00 | 9.00 | 29.97 | 33.62 | 1.54 | |

| | | KA | PV | Knowled ge Elements | Generati ons | RC | NC | ASPL | Valid N (listwise) |
|---|---|---|---|---|---|---|---|---|---|
| | Std. Dev | 0.03 | 6.14 | 49.44 | 2.40 | 8.89 | 16.89 | 0.13 | |
| CNT | Min | 0.00 | 38.29 | 7.00 | 2.00 | 9.07 | 5.38 | 1.11 | 25.00 |
| | Max | 0.28 | 65.58 | 593.00 | 19.00 | 65.63 | 64.21 | 2.15 | |
| | Mean | 0.11 | 50.16 | 247.00 | 14.00 | 25.10 | 28.25 | 1.83 | |
| | Std. Dev | 0.07 | 6.07 | 147.39 | 4.09 | 12.30 | 16.96 | 0.23 | |

Figure 8-3 shows the citation distribution over multiple generations of all the three sectors. Similar to what was discovered by Atallah and Rodríguez (2013) with forward citations, an inverted-U shape distribution in backward citations may be observed. This result however contrasts with the prediction by Bosworth (2004) that tracing citations backwards in time will produce a monotonically increasing number of patents. The reason for this difference could be the time span of the data being observed. Since Bosworth used data from USPTO, the data in that study was limited to the mid-1970's. Hence, Bosworth could observe the backward citations up to 24 years (1976-2000) or five generations only. Using patent data from Espacenet, I was able to observe more than 13 generations of backward citations, which is a more complete picture of the knowledge structure.

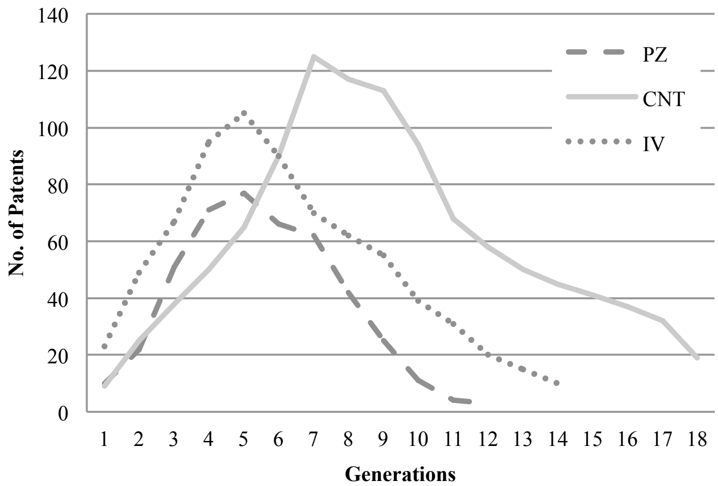



**Figure 8-3: Backward citation distribution of patents over generations**

Following the discussion on structural forms (section 3.4, CHAPTER 3), I investigate the patent citation network of sample US 4952836 of PZ sector. This patent has 107 unique knowledge elements (citations) in its knowledge structure that are spread over 9 generations. The knowledge structure of this patent when $H^m$ type of citation generation is adopted is given in Figure 8-4. As theorized, the structure has a recognizable "eye" form. Further investigation revealed that 32% of the knowledge elements appear multiple times in different generations, resulting in an overall structure that displays 256 knowledge elements. The structural form of this patent based on $G^s$ type of citation generation (Figure 8-5) displays only the unique knowledge elements.

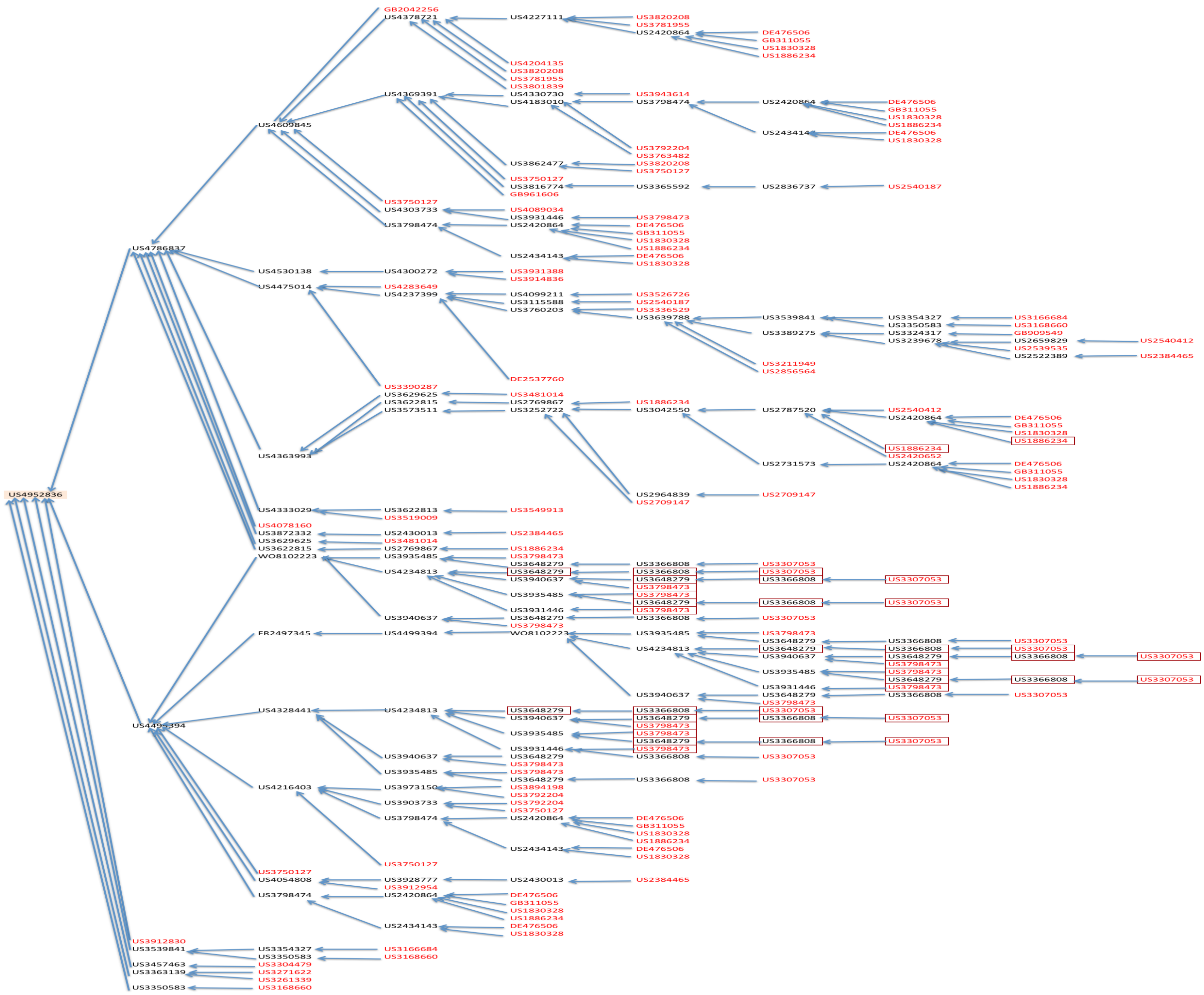


**Figure 8-4: Knowledge structure of US4952836 as per $H^m$ type of citation generation**

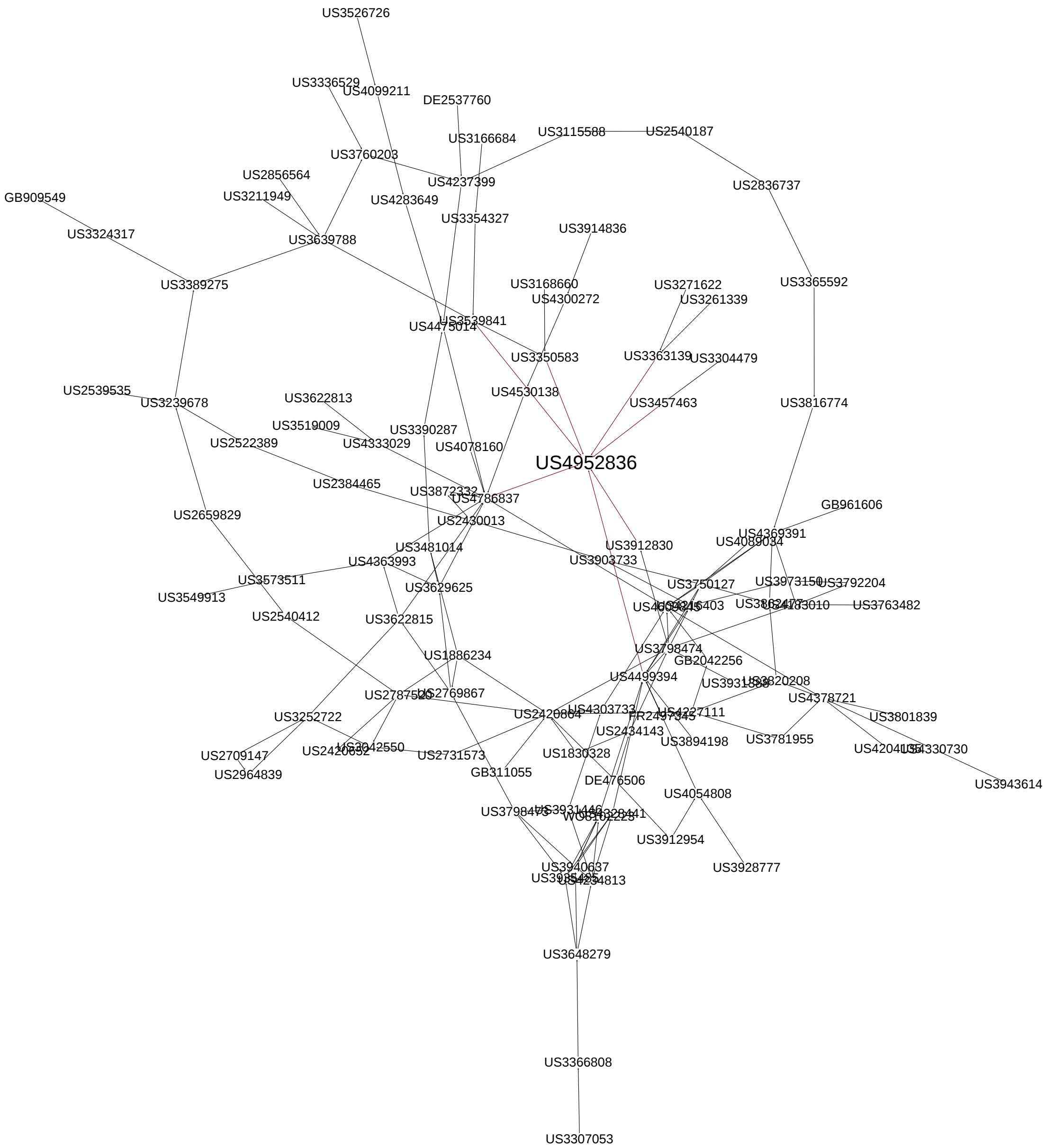



**Figure 8-5: Knowledge structure of US49952836 as per $G^s$ type of citation generation**

## 8.3 Patent Value based on single-level relationships

Many studies have demonstrated that the information contained in the first page of the patent document could be used to predict the value of the invention. A summary of such studies has been presented in TABLE 2-1 of CHAPTER 2. I replicate the methodology of one such study to determine its validity on the sectors chosen in this thesis.

Lin et al. (2007) developed a simple model to predict the number of citations received by a patent using the information from the first page of the patent document. The study covered over 145,000 patents from 14 different patent classes in the field of biotechnology. Amongst other findings, the authors observe that the number of references, the number of claims, and the examination time are all positively correlated with the citations received by the patent. To explain the correlation between examination time and the number of citations received, the authors argue that it may take a longer time for patent examiners to judge whether an important patent should be granted or not. They also observe that the number of claims have a higher explanatory power on citations received. I chose this study because the simplicity of their methodology implies that technology managers can easily utilise it as technology evaluation tool. Also, the patents chosen in that study were based on the patent classifications, which is very similar to the sample selection technique adopted in this thesis.

The study by Lin et al. (2007) predicted the dependent variable (log of 1 plus citations) using five independent variables: log of references, log of claims, examination time, country dummy variable, and state dummy variable. The country dummy variable takes the value 1 if the patent comes from the US else 0. The state dummy variable takes the value of 1 if the patent comes from the state of Massachusetts. Since my sample size is much smaller, I only consider the country variable in my analysis. The results of multiple linear regression are given in TABLE 8-2. The results show that this model significantly predicts the citations in the PZ sector only. Also, for this sector, only the number of claims and examination time are significant predictors. The coefficient of regression for log of references is not statistically significant. For TFP, IV and CNT sectors the results indicate that this model is unable to predict the citations received by the patent.

**TABLE 8-2: Multiple Linear Regression results**

| | TFP | IV | PZ | CNT |
|---|---|---|---|---|
| **Intercept** | (3.139) | (0.725) | (2.9) | (1.527) |
| | 1.018 | 0.325 | 0.643* | 0.765 |
| **References** | (0.009) | (0.108) | (1.238) | (0.564) |
| | 0.002 | 0.027 | 0.218 | 0.259 |
| **Claims** | (0.995) | (1.165) | (2.084) | (0.626) |
| | 0.211 | 0.317 | 0.274* | 0.261 |

| | TFP | IV | PZ | CNT |
|---|---|---|---|---|
| **Examination Time** | (1.111) | (-0.016) | (2.327) | (0.628) |
| | 0.001 | -3.26E-06 | 0* | 0 |
| **US Dummy** | (0.711) | (-0.282) | (-0.087) | (1.118) |
| | 0.105 | -0.046 | -0.007 | 0.312 |
| **No. of Observations** | 45 | 29 | 53 | 25 |
| **F-Value** | 1.027 | 0.414 | 2.87 | 1.361 |
| **p-value** | 0.405 | 0.797 | 0.033 | 0.283 |
| **$R^2$** | 0.093 | 0.065 | 0.193 | 0.214 |

*Note: bracketed values are t-values of regression coefficients and unbracketed values are regression coefficients of corresponding variables.*

** Coefficient significant at 0.05 level*

The discrepancies in the conclusions drawn in the study by Lin et al. (2007) and the results observed for the sample set of this thesis indicate that there may be other factors in play that affect the technical value. Surface-level indicators such as the number of claims or number of references are unable to capture the total effect and hence cannot be relied upon for consistent results. Lin et al. (2007) study only included inventions within the field of biotechnology where as my research examines inventions from three different technological areas that can be categorised as interdisciplinary.

## 8.4 KA results

To observe if KA is able to distinguish between two patents of different technical values, I compare two patents from PZ sector (TABLE 8-3). Application of US 4885499 was filed in 1989 and was granted a patent in the same year. Though this invention was cited only 9 times by subsequent inventions, it can be noted that this invention has an INPADOC family size of 3. This indicates that a legal protection was sought for this invention in three different countries (US, Germany and Japan). Further investigation revealed that the patent remained active for at least 10 years after its filing. This further indicates that the invention was perceived valuable enough by the inventor to continue its legal protection thus, giving an insight into its technical value.

**TABLE 8-3: Comparison of patents from PZ sector**

| | US 4885499 | US 4959580 |
|---|---|---|
| **Filing Date** | 10/2/1989 | 26/2/1987 |
| **Citation** | 9 | 49 |
| **Family Size** | 3 | 1 |
| **Patent life** | Active for 10 years | Ceased |
| **Processing Time (years)** | 0.8 | 3.6 |
| **Knowledge elements** | 144 | 38 |
| **No. of Generations** | 12 | 4 |
| **KA** | 0.077 | 0.021 |
| **No. of inventors** | 3 | 2 |
| **PV** | 57.01 | 49.12 |

Now consider the second patent from this sector. The application for patent US 4959580 was filed in 1987 but was granted a patent in 1990, recording a processing time of 3.6 years. This is the longest processing time observed in the samples of this sector. Lin et al. (2007) argue that examiners may need a longer time in the processing of important patents. The number of citations received by this patent (49), also seem to indicate that the invention may be of high value. However, a different picture is revealed through the patent family of the invention. Though this patent has 4 additional INPADOC family members, this invention was granted a patent in only 2 other jurisdictions. The application was eventually withdrawn in the remaining 2 countries. The granted patents too did not complete their term and ceased due to non-payment of fees within the first 10 years of their life. This indicates that at some point the technical value of this invention may have been deemed unfit for further commercial exploration.

Investigation of the knowledge structure revealed that the first patent resulted from 7 generations of knowledge elements that amount to 55 patents. On the other hand, 38 other knowledge elements had influenced the creation of the second invention. The first patent thus, recorded a KA of 0.077 while the second patent scored a lower value of 0.021. A higher KA in the first patent indicates that the invention encompasses more knowledge existing in the sector. As a result, more know-how and experiences contributed towards the creation of this invention. Thus, the first patent shows higher knowledge accumulation as compared to the second patent. These initial observations indicate that KA may provide a distinguishing characteristic to separate high technical value inventions from that of low technical value.

### 8.4.1 KA correlation and regression results

I use Eq. (6-3) and Eq. (6-2) described in CHAPTER 6 to calculate KA and PV, respectively, for the sample sets. Shapiro-Wilk tests for normality (TABLE 8-4) showed that the distributions of both KA and PV do not deviate from normal in IV and CNT sectors. In the PZ sector, I find that only the distribution of KA conforms to normality. In the TFP sector, distributions of both KA and PV deviate from normal. Thus, I perform Pearson correlation tests between KA and PV for the sectors IV and CNT. For the PZ and TFP sectors, due to non-normal distributions, I perform the non-parametric test, Spearman's-rho correlation, in addition to Pearson correlation test.

**TABLE 8-4: Shapiro-Wilk Tests of Normality**

| | | **KA** | **PV** |
|---|---|---|---|
| **TFP** | Statistic | 0.935 | 0.938 |
| | df | 45 | 45 |
| | Sig. | 0.015 | 0.018 |
| **IV** | Statistic | 0.935 | 0.929 |
| | df | 29 | 29 |
| | Sig. | *0.073* | *0.053* |
| **PZ** | Statistic | 0.957 | 0.955 |

| | | KA | PV |
|---|---|---|---|
| | df | 54 | 54 |
| | Sig. | *0.053* | 0.042 |
| CNT | Statistic | 0.965 | 0.968 |
| | df | 26 | 26 |
| | **Sig.** | *0.489* | *0.577* |

Results from the Pearson correlation test (TABLE 8-5) show that there is a significantly positive correlation between KA and PV in all the three sectors *(IV: $r = .489, p < .01$; PZ: $r = .423, p < .01$; CNT: $r = .477, p < .05$)*. Spearman's rho correlation test (TABLE 8-6) further confirms the correlation in the PZ and TFP sectors. The strength of the correlation is strongest in the IV sector and weakest in the TFP sector. While statistical significance informs us of how likely it is that the result is due to chance, effect size informs us of the importance of the result. Effect size is a statistical concept that measures the strength of the relationship of two variables. According to Cohen (1992) a correlation coefficient value between 0.3 and 0.5 represents a moderate effect size. Thus, a medium effect size can be seen in all the four sectors. This supports my first hypothesis that knowledge accumulation is an indicator of the technical value of a patent.

**TABLE 8-5: Pearson Correlation Test**

| | | PV | | |
|---|---|---|---|---|
| | | IV | PZ | CNT |
| KA | Pearson Correlation | 0.489** | 0.423** | 0.477* |
| | Sig. (2-tailed) | 0.007 | 0.001 | 0.014 |
| | N | 29 | 54 | 26 |

*** Correlation is significant at the 0.01 level (2-tailed).*

** Correlation is significant at the 0.05 level (2-tailed).*

**TABLE 8-6: Spearman's rho Correlations for PZ sector**

| | | PV | |
|---|---|---|---|
| | | TFP | PZ |
| KA | Correlation Coefficient | 0.323* | 0.396** |
| | Sig. (2-tailed) | 0.03 | 0.003 |
| | N | 45 | 54 |

** Correlation is significant at the 0.05 level (2-tailed).*

*** Correlation is significant at the 0.01 level (2-tailed).*

I then performed a multiple linear regression analysis to evaluate KA in predicting PV and to determine the effect of sector on PV. For this analysis, in order to maintain an equal sample size in all the three sectors, I randomly selected 25 cases from IV, TFP and PZ sectors. I then introduced three dummy variables DTFP, DIV, DPZ and DCNT to represent the sectors TFP, IV, PZ and CNT, respectively. Thus, I evaluated PV using the following equation:

$$PV = B_0 + B_{KA}KA + B_{TFP}DTFP + B_{IV}DIV + B_{PZ}DPZ + B_{CNT}DCNT + \varepsilon \quad (8\text{-}1)$$

where $B_0$, $B_{KA}$, $B_{TFP}$, $B_{IV}$, $B_{PZ}$, $B_{CNT}$ are constants and ε is the error term. The results (TABLE 8-7) indicate a significant regression equation *($F(4,95) = 2.845$, $p < 0.05$),* with an $R^2$ of 0.107. The effect size for this analysis ($f^2$=0.012) was found to conform to a small effect as per Cohen (1992). While the variance explained by this relationship is very low, further discussion in Section 8.6 (TABLE 8-22), shows that these results are comparable with other similar studies in the field. Coefficients of regression for KA *($B_{KA}$ =10.467, $t(95) = 2.924$, $p < 0.01$)* indicates that it is a significant predictor of patent value. The coefficients of regression for sectors DTFP, DCNT and DPZ did not achieve significance. However, a significant coefficient of regression was observed in IV sector *($B_{IV}$ = -7.812, $t(95)$= -2.766, $p < 0.01$).* Thus, it may be concluded that some sectors contribute significantly towards the technical value while others do not.

**TABLE 8-7: Multiple Linear Regression Analysis**

| R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|
| .327[a] | 0.107 | 0.069 | 5.79308 |

*a Predictors: (Constant), DTFP, KA, DCNT, DIV*

| ANOVA [a] | | | | | |
|---|---|---|---|---|---|
| | Sum of Squares | df | Mean Square | F | Sig. |
| **Regression** | 381.96 | 4 | 95.49 | 2.845 | .028[b] |
| **Residual** | 3188.181 | 95 | 33.56 | | |
| **Total** | 3570.141 | 99 | | | |

*a Dependent Variable: PV*

*b Predictors: (Constant), DTFP, KA, DCNT, DIV*

| Coefficients [a] | | | | | |
|---|---|---|---|---|---|
| | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
| | B | Std. Error | Beta | | |
| **(Constant)** | 51.192 | 1.175 | | 43.586 | 0 |
| **KA** | 10.467 | 3.579 | 0.566 | 2.924 | 0.004 |
| **DIV** | -9.983 | 2.987 | -0.723 | -3.342 | 0.001 |
| **DCNT** | -2.171 | 1.65 | -0.157 | -1.315 | 0.192 |
| **DTFP** | -2.254 | 1.698 | -0.163 | -1.328 | 0.187 |

*a Dependent Variable: PV*

| Excluded Variables [a] | | | | | |
|---|---|---|---|---|---|
| | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics |
| | | | | | Tolerance |
| **DPZ** | .b | . | . | . | 0 |

*a Dependent Variable: PV*

*b Predictors in the Model: (Constant), DTFP, KA, DCNT, DIV*

### 8.4.2 Comparison of KA with other technical value indicators

In the next step, I tested the correlation between KA and other patent value indicators mentioned in the literature. Studies have attempted to define the technical value of an invention in various ways. This has resulted in a number of different value indicators. It is yet unclear whether these indicators together represent the total technical value or if each one represents some aspect of the technical value. In case of the second scenario, with the increasing number of these indicators, the probability of multicollinearity between them also increases. Hence, it is important to determine whether KA is indeed a new type of value indicator or it is detecting value that is already measured by an existing indicator.

In order to do so, I first calculated the patent technical value based on the indicators described in Section 6.6 of CHAPTER 6. TABLE 8-8 presents the Pearson correlation results of KA and other value indicators of CNT sector. The results show a significant positive correlation between KA and value indicators TII and IMPORTB. Such correlation is not observed between KA-Generality, KA-Originality and KA-TCT. Collinearity statistics (TABLE 8-9) shows a high VIF (Variance Inflation Factor) values for variables TII *(VIF=16.845, Tolerance =0.059)* and IMPORTB *(VIF=17.059, Tolerance = 0.059).* A VIF values exceeding 10 is considered to indicate multicollinearity. Thus, collinearity exist between TII and IMPORTB. I do not observe such high values for KA.

**TABLE 8-8: Pearson correlation between patent value indicators for CNT sector**

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| **Generality** | Pearson Correlation | 1 | 0.068 | .414* | -.401* | 0.371 | 0.084 |
| | Sig. (2-tailed) | | 0.745 | 0.039 | 0.047 | 0.068 | 0.691 |
| | N | 25 | 25 | 25 | 25 | 25 | 25 |
| **Originality** | Pearson Correlation | 0.068 | 1 | 0.359 | -0.023 | 0.319 | 0.293 |
| | Sig. (2-tailed) | 0.745 | | 0.078 | 0.915 | 0.12 | 0.156 |
| | N | 2.50E+01 | 25 | 25 | 25 | 25 | 25 |
| **TII** | Pearson Correlation | .414* | 0.359 | 1 | -0.249 | .964** | .470* |
| | Sig. (2-tailed) | 0.039 | 0.078 | | 0.23 | 0 | 0.018 |
| | N | 25 | 25 | 25 | 25 | 25 | 25 |
| **TCT** | Pearson Correlation | -.401* | -0.023 | -0.249 | 1 | -0.226 | -0.148 |
| | Sig. (2-tailed) | 0.047 | 0.915 | 0.23 | | 0.278 | 0.48 |
| | N | 25 | 25 | 25 | 25 | 25 | 25 |
| **IMPORTB** | Pearson Correlation | 0.371 | 0.319 | .964** | -0.226 | 1 | .478* |
| | Sig. (2-tailed) | 0.068 | 0.12 | 0 | 0.278 | | 0.016 |

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| | N | 25 | 25 | 25 | 25 | 25 | 25 |
| **KA** | Pearson Correlation | 0.084 | 0.293 | .470* | -0.148 | .478* | 1 |
| | Sig. (2-tailed) | 0.691 | 0.156 | 0.018 | 0.48 | 0.016 | |
| | N | 25 | 25 | 25 | 25 | 25 | 25 |

** Correlation is significant at the 0.05 level (2-tailed).*

*** Correlation is significant at the 0.01 level (2-tailed).*

**TABLE 8-9: Collinearity Statistics**

| | TFP | | IV | | PZ | | CNT | |
|---|---|---|---|---|---|---|---|---|
| | **Tolerance** | **VIF** | **Tolerance** | **VIF** | **Tolerance** | **VIF** | **Tolerance** | **VIF** |
| **Generality** | 0.83 | 1.205 | 0.882 | 1.134 | 0.813 | 1.229 | 0.652 | 1.533 |
| **Originality** | 0.885 | 1.131 | 0.828 | 1.208 | 0.571 | 1.75 | 0.791 | 1.264 |
| **TII** | 0.082 | 12.265 | 0.039 | 25.435 | 0.031 | 32.52 | 0.059 | 16.845 |
| **TCT** | 0.9 | 1.111 | 0.748 | 1.337 | 0.577 | 1.734 | 0.815 | 1.227 |
| **IMPORTB** | 0.093 | 10.811 | 0.043 | 23.484 | 0.033 | 30.64 | 0.059 | 17.059 |
| **KA** | 0.638 | 1.567 | 0.692 | 1.446 | 0.583 | 1.716 | 0.732 | 1.367 |

*a Dependent Variable: PV*

The correlation matrix for the PZ sector is given in TABLE 8-10. In addition to a positive correlation between KA-TII and KA-IMPORTB, a negative correlation between KA-TCT is noted in this sector. The correlation is found to be statistically significant (*$r = -0.386$, $p < .01$).* Technology cycle time (TCT) is defined as the length of time it takes a firm to use a new technology. It is measured as median age of the patents cited by a given patent (Narin, 1993). The measure of TCT depends primarily on the knowledge base of a firm. Bierly and Chakrabarti (1996) showed that a high knowledge base level in a firm will lead to faster technology cycle time by allowing members of the firm to better understand and interpret external advances in the field and allowing the firm to combine new technologies with other complementary technologies. Hence, a high KA may lead to a lower TCT value. However, collinearity statistics (TABLE 8-9) does not indicate multicollinearity with KA.

**TABLE 8-10: Pearson Correlation for patent value indicators for PZ sector**

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| **Generality** | Pearson Correlation | 1 | 0.266 | 0.116 | .301* | 0.161 | -0.127 |
| | Sig. (2-tailed) | | 0.054 | 0.407 | 0.029 | 0.248 | 0.366 |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |
| **Originality** | Pearson Correlation | 0.266 | 1 | .419** | .454** | .387** | 0.136 |
| | Sig. (2-tailed) | 0.054 | | 0.002 | 0.001 | 0.004 | 0.331 |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |
| **TII** | Pearson | 0.116 | .419** | 1 | 0.017 | .981** | .479** |

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| | Correlation | | | | | | |
| | Sig. (2-tailed) | 0.407 | 0.002 | | 0.901 | 0 | 0 |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |
| **TCT** | Pearson Correlation | .301* | .454** | 0.017 | 1 | 0.023 | -.386** |
| | Sig. (2-tailed) | 0.029 | 0.001 | 0.901 | | 0.869 | 0.004 |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |
| **IMPORTB** | Pearson Correlation | 0.161 | .387** | .981** | 0.023 | 1 | .446** |
| | Sig. (2-tailed) | 0.248 | 0.004 | 0 | 0.869 | | 0.001 |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |
| **KA** | Pearson Correlation | -0.127 | 0.136 | .479** | -.386** | .446** | 1 |
| | Sig. (2-tailed) | 0.366 | 0.331 | 0 | 0.004 | 0.001 | |
| | N | 53 | 53 | 53 | 53 | 53 | 53 |

** Correlation is significant at the 0.05 level (2-tailed).*

*** Correlation is significant at the 0.01 level (2-tailed).*

In the IV sector, no correlation was observed between KA and any other existing value indicators (TABLE 8-11). Similar to that in CNT sector, a correlation of moderate effect size was observed between KA-TII and KA-IMPORTB in TFP sector (TABLE 8-12). Multicollinearity is not observed between KA and any of the value indicators across all the four sectors. These observations indicate that KA is a new type of metric for the technical value of invention. The lack of correlation or multicollinearity between KA and existing value indicators implies that KA is measuring a different construct of the technical value, which is not measured by the existing indicators.

**TABLE 8-11: Pearson Correlation for patent value indicators for IV sector**

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| **Generality** | Pearson Correlation | 1 | -0.054 | 0.075 | 0.157 | 0.031 | -0.222 |
| | Sig. (2-tailed) | | 0.782 | 0.699 | 0.417 | 0.874 | 0.248 |
| | N | 29 | 29 | 29 | 29 | 29 | 29 |
| **Originality** | Pearson Correlation | -0.054 | 1 | .377* | 0.026 | 0.344 | 0.186 |
| | Sig. (2-tailed) | 0.782 | | 0.044 | 0.892 | 0.068 | 0.335 |
| | N | 29 | 29 | 29 | 29 | 29 | 29 |
| **TII** | Pearson Correlation | 0.075 | .377* | 1 | 0.252 | .976** | 0.332 |
| | Sig. (2-tailed) | 0.699 | 0.044 | | 0.188 | 0 | 0.078 |
| | N | 29 | 29 | 29 | 29 | 29 | 29 |
| **TCT** | Pearson Correlation | 0.157 | 0.026 | 0.252 | 1 | 0.212 | -0.299 |
| | Sig. (2-tailed) | 0.417 | 0.892 | 0.188 | | 0.268 | 0.115 |

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| | N | 29 | 29 | 29 | 29 | 29 | 29 |
| **IMPORTB** | Pearson Correlation | 0.031 | 0.344 | .976** | 0.212 | 1 | 0.331 |
| | Sig. (2-tailed) | 0.874 | 0.068 | 0 | 0.268 | | 0.079 |
| | N | 29 | 29 | 29 | 29 | 29 | 29 |
| **KA** | Pearson Correlation | -0.222 | 0.186 | 0.332 | -0.299 | 0.331 | 1 |
| | Sig. (2-tailed) | 0.248 | 0.335 | 0.078 | 0.115 | 0.079 | |
| | N | 29 | 29 | 29 | 29 | 29 | 29 |

** Correlation is significant at the 0.05 level (2-tailed).*

*** Correlation is significant at the 0.01 level (2-tailed).*

**TABLE 8-12: Pearson Correlation for patent value indicators for TFP sector**

| | | Generality | Originality | TII | TCT | IMPORTB | KA |
|---|---|---|---|---|---|---|---|
| **Generality** | Pearson Correlation | 1 | 0.172 | 0.24 | -0.171 | 0.154 | 0.062 |
| | Sig. (2-tailed) | | 0.26 | 0.113 | 0.262 | 0.313 | 0.686 |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |
| **Originality** | Pearson Correlation | 0.172 | 1 | 0.104 | 0.037 | 0.109 | -0.208 |
| | Sig. (2-tailed) | 0.26 | | 0.495 | 0.809 | 0.474 | 0.171 |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |
| **TII** | Pearson Correlation | 0.24 | 0.104 | 1 | -0.085 | .947** | .482** |
| | Sig. (2-tailed) | 0.113 | 0.495 | | 0.58 | 0 | 0.001 |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |
| **TCT** | Pearson Correlation | -0.171 | 0.037 | -0.085 | 1 | -0.089 | -0.239 |
| | Sig. (2-tailed) | 0.262 | 0.809 | 0.58 | | 0.559 | 0.114 |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |
| **IMPORTB** | Pearson Correlation | 0.154 | 0.109 | .947** | -0.089 | 1 | .411** |
| | Sig. (2-tailed) | 0.313 | 0.474 | 0 | 0.559 | | 0.005 |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |
| **KA** | Pearson Correlation | 0.062 | -0.208 | .482** | -0.239 | .411** | 1 |
| | Sig. (2-tailed) | 0.686 | 0.171 | 0.001 | 0.114 | 0.005 | |
| | N | 45 | 45 | 45 | 45 | 45 | 45 |

*** Correlation is significant at the 0.01 level (2-tailed).*

At this point it is important to highlight the differences between KA and other indicators. Generality measures the technical value through the descendants of the technology and their spread in the technical areas. Since the number of descendants of a technology increase with time, the Generality of a technology is not constant. This makes it an unsuitable indicator for evaluating new technologies. The computation of TII and IMPORTB utilizes both backward and forward citations. These indicators suffer the same disadvantages that other forward citations-based indicators do. It should also be noted that TII and IMPORTB only consider the immediate knowledge (first level references) that has led to the invention. These indicators ignore the indirect effects of knowledge elements on technical value. Originality measures the diversity of the knowledge roots by utilizing both the backward citations and their IPC. This indicator does not account for the quantity or the age of the knowledge. The measure of KA takes into account the entire knowledge foundation of the invention, unlike TII and IMPORTB. This indicator also accounts for the age of the knowledge. As discussed in CHAPTER 5, the age of the knowledge preceding an invention has been shown to be of importance in the conception of inventions. Moreover, the value of KA does not change with time, as its measurement does not depend on forward citations. This quality makes it an ideal technical value indicator for the newly granted patents.

## 8.5 STRUCTURAL ROBUSTNESS results

To illustrate how the robustness of the knowledge structure varies with patent value, I compare the robustness measures of a low value patent with a high value patent from CNT sector (TABLE 8-13). Patent US6183714 describes a process of making single-wall carbon nanotubes by vaporization process using lasers while US 6386468 describes a process of fullerene fluorination through mechano-chemical process. The first invention, with a patent value of 65.58 has accrued 279 citations and has been granted protection in 5 jurisdictions. On the other hand, the second invention has accrued 7 citations with a patent value of 38.29. The patent protection of this invention did not complete its full term due to non-payment of fee. This further indicates the low technical value of this invention.

**TABLE 8-13: Comparison of patents**

| | **CNT** | | **PZ** | |
|---|---|---|---|---|
| | **US 6183714** | **US6386468** | **US 4876776** | **US 4912351** |
| **Filing Date** | 26/7/1996 | 29/11/1999 | 11/02/1988 | 22/09/1988 |
| **Citation** | 279 | 7 | 29 | 29 |
| **Family Size** | 11 | 3 | 2 | 4 |
| **Patent life** | Completed term | Expired due to non-payment of fees | Expired due to non-payment of fees | Completed term |
| **Processing Time** | 4.5 | 2.5 | 1.7 | 1.5 |
| **Knowledge elements** | 334 | 76 | 23 | 107 |
| **No. of Generations** | 16 | 8 | 4 | 10 |
| **KA** | 0.1846 | 0.0264 | 0.01 | 0.056 |
| **No. of inventors** | 6 | 3 | 3 | 4 |
| **RC** | 37.59 | 9.07 | 26.28 | 32.37 |
| **ASPL** | 1.98 | 1.63 | 1.447 | 1.583 |
| **NC** | 54.38 | 10.53 | 26.09 | 48.15 |
| **PV** | 65.58 | 38.29 | 43.78 | 56.97 |

The structural robustness analysis of these two inventions is given in Figure 8-6. The first invention demonstrated a RC of 37.59 as compared to the second invention with a RC of 9.07. In the first invention, the target patent detached from the giant cluster after the removal of 51% nodes. Such a detachment occurred at the removal of just 4% nodes in the second invention. The red marker on the graph indicates the point where the target patent detached from the giant cluster. The results indicate that the knowledge structure of the first invention is more robust and therefore should lead to higher knowledge appropriation. In this example, the vast difference in the patent values is also apparent through the citation counts. However, the use of citation counts for value assessment is post-hoc in nature.

Now consider the example of two patents from PZ sector with similar citation counts. Patents US 4876776 and US 4912351 have been cited 29 times till date. Any technique that relies on simple citation counts would grade these two patents as equal in value. However, further investigation showed that the former patent lapsed after 9 years of its filing due to non-payment of fee, while the latter completed its full term. This is reflected in their patent values *($PV_{4876776}$=43.78, $PV_{4912351}$=56.97)*. The first patent registered a RC of 26.28. The target patent detached from the giant cluster at the removal of 26% of the nodes. On the other hand, the second patent registered a RC of 32.37 and NC 48%. These examples clearly show that the robustness measure is better able to distinguish valuable patents that may appear to be similar in value by techniques that rely on simple citation counts alone.

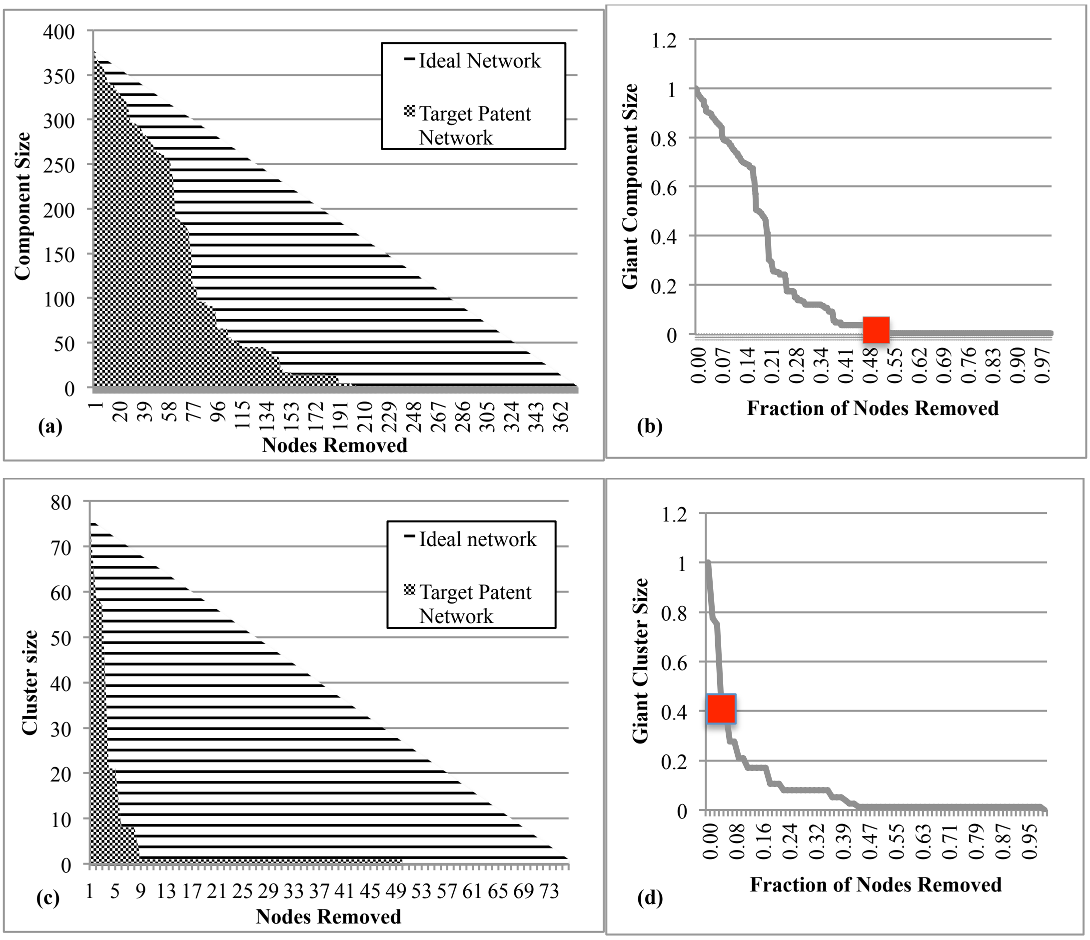



**Figure 8-6: (a) RC of US6183714 (b) Disintegration profile of US6183714 (c) RC of US6386465 (d) Disintegration profile of US6386465**

### 8.5.1 Robustness correlation and regression results

Before performing the robustness measurements, it is important to first characterise the patent citation networks to confirm the node removal strategy as justified in the methodology section. I examined the small-world properties of the citation networks. I randomly analysed 10% of the samples from each sector as per the technique described in Section 6.7.1 of CHAPTER 6. It was observed that in each sector, the criterion $\lambda \approx 1$ and $\gamma > 1$ was met by the samples (TABLE 8-14). This confirms that the knowledge structure of the samples may be considered to be small-world networks.

**TABLE 8-14: Small-World network characterization of samples**

| Sector | Patent No. | L | CC | $L_r$ | $CC_r$ | λ | γ |
|---|---|---|---|---|---|---|---|
| PZ | US4814660 | 2.33 | 0.071 | 2.335 | 0.0278 | 0.99 | 2.68 |
| | US4885499 | 2.99 | 0.039 | 2.389 | .011 | 1.25 | 3.54 |
| | US4912351 | 2.446 | 0.041 | 2.2807 | 0.0162 | 1.07 | 2.77 |
| | US5004945 | 3.108 | 0.037 | 2.2474 | 0.0138 | 1.40 | 4.22 |
| | US5056201 | 2.981 | 0.049 | 2.4244 | 0.012 | 1.23 | 4.93 |
| CNT | US6157043 | 4.242 | 0.052 | 2.728 | 0.005 | 1.56 | 10.57 |
| | US6479028 | 4.111 | 0.104 | 3.3963 | 0.0068 | 1.17 | 21.39 |
| IV | US7554224 | 2.701 | 0.114 | 2.1827 | 0.0214 | 1.24 | 11.17 |
| | US8080906 | 2.612 | 0.081 | 2.1721 | 0.0252 | 1.22 | 3.93 |
| | US6930414 | 2.4 | 0.107 | 2.0874 | 0.0344 | 1.15 | 3.36 |
| TFP | US4892592 | 4.19 | 0.05 | 3.3904 | 0.003 | 1.23 | 19.33 |
| | US5112410 | 3.527 | 0.056 | 2.6591 | 0.0074 | 1.33 | 8.27 |
| | US5155565 | 4.107 | 0.067 | 3.642 | 0.0028 | 1.12 | 25.12 |
| | US4929281 | 3.358 | 0.051 | 2.828 | 0.009 | 1.18 | 5.66 |

The next step in the analysis was to determine whether the citation networks might be characterised as scale-free. In a scale free network, the node degree distribution conforms to power law and is represented by the equation

$$p(k) \sim k^{-\propto}$$

where *p(k)* fraction of nodes in the network having k connections to other nodes. According to Clauset et al. (2009), the exponent (α) for scale free networks typically lies between $2<\alpha<3$. Analysis of the node distribution of the sample sets however revealed that the average of power law exponent is less than 1 for all the sectors (TABLE 8-15). Thus, the citation network of the sample sets cannot be considered "perfectly" scale-free. Furthermore, the node distribution cannot be considered homogenous (as is the characteristic of a random network) since the average Gini coefficient of the samples is greater than 0 ($G_{CNT}=0.443$, $G_{PZ} = 0.407$, $G_{IV}=0.3$, $G_{TFP}=0.45$). The Gini coefficient describes the heterogeneity of the node degree distribution. The value of G varies between 0 and 1 with 0 indicating a homogenous distribution (Kunegis & Preusse, 2012).

**TABLE 8-15: Power-law exponent**

| | TFP | IV | CNT | PZ |
|---|---|---|---|---|
| **Min** | 4.6455E-11 | 3.66003E-14 | 1.61918E-11 | 0.02 |
| **Max** | 1.05 | 1.00 | 0.68 | 0.85 |
| **Mean** | 0.65 | 0.17 | 0.43 | 0.46 |
| **Std. Dev** | 0.37 | 0.20 | 0.21 | 0.20 |
| **Valid N (listwise)** | 45 | 29 | 25 | 53 |

Thus, to determine the node-removal strategy, I perform both targeted and random node removal on the samples of IV sector. I chose this sector since it is the least scale-free, displaying an average power law exponent of 0.17 *(SD=0.2)*. The aim is to choose the strategy that is most damaging to the network. Figure 8-7 shows the profile of the giant component of sample US 7554224 under targeted and random attacks. It is clearly observed that the size of the giant component reduces much more linearly in the case of random node removal, indicating that targeted node removal is more damaging to the network. It was further noted that the network disintegrated when 75% of the nodes were removed randomly. On the other hand, under targeted attack, the network disintegrated after the removal of only 4% of the nodes. This behaviour was observed in all the other samples of this sector. Therefore, I choose targeted node removal strategy to measure robustness of all the target patents.

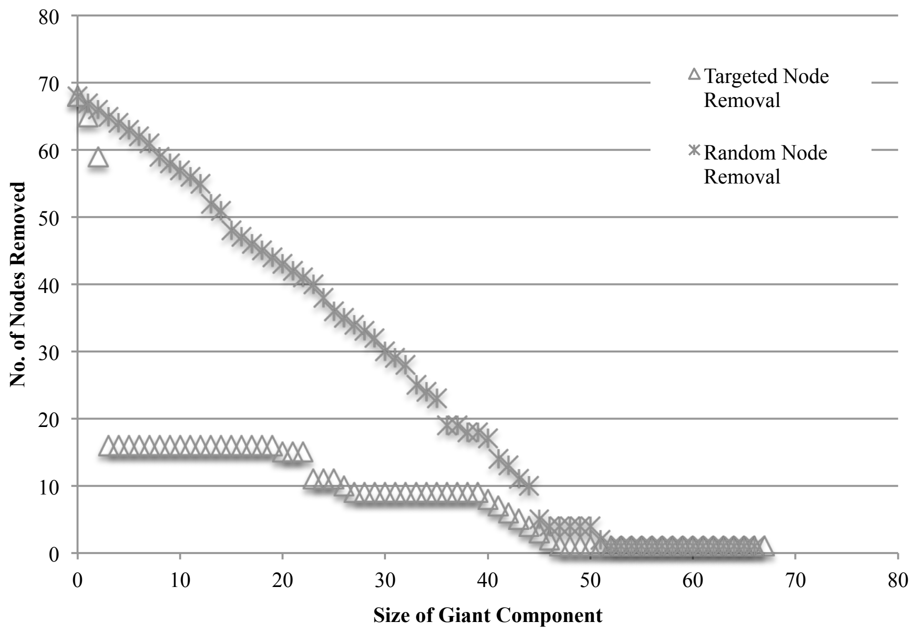



**Figure 8-7: Comparison of targeted and random node removal in US7554224**

Having decided the node removal strategy, I then computed the robustness metrics (NC, RC and ASPL) of all samples by deleting the nodes as per their betweenness centrality. Shapiro-Wilk test for normality (TABLE 8-16) reveals in TFP and CNT sectors normal distributions was observed in NC, while in PZ sector only the distribution of ASPL conformed to normality. The distribution of rest of the indicators is non-normal. Thus, I perform Spearman's rho correlation test between PV and the robustness indicators.

The results (TABLE 8-17) indicate that all the three indicators RC, NC and ASPL significantly correlate with PV in TFP, PZ and CNT sectors. In IV sector, only ASPL shows a statistically significant correlation with PV. A small to medium effect size is seen in TFP ($r_{RC}=0.28, r_{NC}=0.277, r_{ASPL}=0.412$), IV ($r_{ASPL}=0.363$) and PZ ($r_{RC}=0.229, r_{NC}=0.315, r_{ASPL}=0.449$) sectors, while a medium to large effect size is observed in CNT sector ($r_{RC}=0.651, r_{NC}=0.442, r_{ASPL}=0.563$). This confirms my second hypothesis that knowledge appropriation in inventions has a positive correlation with their technical value. The correlations are strongest in the CNT sector with RC displaying the largest correlation coefficient ($r_{RC}=0.651, p<0.01$).

**TABLE 8-16: Shapiro-Wilk test of normality for STRUCTURAL ROBUSTNESS indicators**

| | **TFP** | | | **IV** | | | **PZ** | | | **CNT** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Statistic* | *df* | *Sig.* | *Statistic* | *df* | *Sig.* | *Statistic* | *df* | *Sig.* | *Statistic* | *df* | *Sig.* |
| **RC** | 0.94 | 45 | 0.024 | 0.841 | 29 | 0.001 | 0.93 | 53 | 0.004 | 0.88 | 25 | 0.01 |
| **NC** | 0.97 | 45 | 0.301 | 0.886 | 29 | 0.005 | 0.95 | 53 | 0.04 | 0.94 | 25 | 0.193 |
| **ASPL** | 0.89 | 45 | 0.001 | 0.863 | 29 | 0.001 | 0.97 | 53 | 0.122 | 0.89 | 25 | 0.011 |

**TABLE 8-17: Spearman's rho correlation test for PV and robustness indicators**

| | **PV** | | | |
|---|---|---|---|---|
| | **TFP** | **IV** | **PZ** | **CNT** |
| **RC** | .281* | 0.159 | .229* | .651** |
| | 0.031 | 0.206 | 0.049 | 0 |
| | 45 | 29 | 53 | 25 |
| **NC** | .277* | 0.115 | .315* | .442* |
| | 0.033 | 0.277 | 0.011 | 0.013 |
| | 45 | 29 | 53 | 25 |
| **ASPL** | .412** | .456** | .449** | .563** |
| | 0.002 | 0.006 | 0 | 0.002 |
| | 45 | 29 | 53 | 25 |

** Correlation is significant at the 0.05 level (1-tailed).*
*** Correlation is significant at the 0.01 level (1-tailed).*

I then performed a forward regression in order to determine the best model for predicting patent technical value based on the robustness of its knowledge structure. The results are displayed in TABLE 8-18. Since in IV sector only ASPL showed a statistically significant correlation with PV, simple linear regression was performed for this sector. The results show that in the PZ and TFP sectors, the best model is achieved using the indicator ASPL. Analysis of the CNT sector yielded two statistically significant models. In Model 1 RC was the best predictor while in Model 2 RC and ASPL together contribute significantly to the patent value. Model 2, however, explains the most variance in PV. Of the two predictors in this model, ASPL is the strongest *($B_{ASPL}$=15.657, t (53)=4.062)*.

ASPL approximates knowledge appropriation in terms of path length between knowledge elements, while RC and NC do so in terms of connectivity within the knowledge network. The results imply that in all the sectors knowledge appropriation is enhanced when the distance between the knowledge elements is shorter. A shorter path length may ensure an efficient knowledge flow without loss of information and therefore lead to better knowledge appropriation.

**TABLE 8-18: Forward regression analysis for predicting PV**

| | TFP | IV | PZ | CNT | |
|---|---|---|---|---|---|
| | *Model 1* | *Model 1* | *Model 1* | *Model 1* | *Model 2* |
| **(Constant)** | (6.344) 34.789 | 2.408(23.057) | (1.788) 15.764 | (17.654) 44.104 | (1.748) 13.571 |
| **RC** | - | - | - | (2.689) 0.241 | (4.375) 0.313 |
| **NC** | - | - | - | - | - |
| **ASPL** | (2.817) 8.494 | 2.831(16.894) | (3.904) 22.02 | - | (4.062) 15.657 |
| **$R^2$** | 0.156 | 0.229 | 0.23 | 0.239 | 0.565 |
| **Adjusted $R^2$** | 0.136 | 0.2 | 0.215 | 0.206 | 0.526 |
| **F** | 7.936 | 8.017 | 15.244 | 7.232 | 14.3 |
| **p-value** | 0.007 | 0.009 | 0.001 | 0.013 | 0.001 |
| **No. of Observations** | 45 | 29 | 53 | 25 | 25 |

*Note: bracketed values are t-values of regression coefficients and unbracketed values are regression coefficients of corresponding variables.*
*a Dependent Variable: PV*

## 8.6 Overall regression

In the final part of the analysis, I investigate how KA and STRUCTURAL ROBUSTNESS together influence PV. For this analysis I first assess the relationship between KA and STRUCTURAL ROBUSTNESS to rule out multicollinearity. Multicollinearity between predictor variables poses a problem in interpreting the effects of individual predictors in a regression analysis. Hence, I perform Spearman's rho correlation test between KA and the robustness indicators RC, NC and ASPL. The results (TABLE 8-19) indicate a strong positive correlation between KA-ASPL in the PZ sector *(r (53)=0.691, $p<0.003$)* and TFP sector *(r (45)=0.874, $p<0.001$)*. No correlation is detected in CNT and IV sectors between KA and any of the robustness indicators. For further confirmation, a collinearity diagnostic was performed. A tolerance value of less than 0.1 and a VIF greater than 10 indicates significant multicollinearity. The results (TABLE 8-20) of the dataset do not indicate the presence of multicollinearity between KA and STRUCTURAL ROBUSTNESS. This thus, validates that KA and STRUCTURAL ROBUSTNESS measure different aspects of PV.

**TABLE 8-19: Spearman's rho correlation between KA and STRUCTURAL ROBUSTNESS indicators**

| | | KA | | | |
|---|---|---|---|---|---|
| | | TFP | IV | PZ | CNT |
| RC | Correlation Coefficient | 0.255 | 0.254 | -0.064 | 0.301 |
| | Sig. (2-tailed) | 0.091 | 0.184 | 0.651 | 0.144 |
| | N | 45 | 29 | 53 | 25 |
| NC | Correlation Coefficient | 0.278 | 0.364 | 0.041 | -0.192 |
| | Sig. (2-tailed) | 0.064 | 0.052 | 0.773 | 0.359 |
| | N | 45 | 29 | 53 | 25 |
| ASPL | Correlation Coefficient | .874** | 0.346 | .691** | 0.329 |
| | Sig. (2-tailed) | 0.001 | 0.066 | 0.001 | 0.108 |
| | N | 45 | 29 | 53 | 25 |

*** Correlation is significant at the 0.01 level (2-tailed).*

**TABLE 8-20: Collinearity Statistics for KA and STRUCTURAL ROBUSTNESS indicators**

| | TFP | | IV | | PZ | | CNT | |
|---|---|---|---|---|---|---|---|---|
| | Tolerance | VIF | Tolerance | VIF | Tolerance | VIF | Tolerance | VIF |
| KA | 0.225 | 4.45 | 0.504 | 1.985 | 0.426 | 2.349 | 0.597 | 1.676 |
| RC | 0.169 | 5.924 | 0.281 | 3.553 | 0.342 | 2.925 | 0.383 | 2.614 |
| NC | 0.175 | 5.715 | 0.308 | 3.242 | 0.326 | 3.066 | 0.388 | 2.579 |
| ASPL | 0.205 | 4.873 | 0.41 | 2.438 | 0.399 | 2.504 | 0.662 | 1.512 |

*a Dependent Variable: PV*

Finally, I perform a multiple-regression utilising the indicators, KA and STRUCTURAL ROBUSTNESS, to determine the best model to predict PV. The results are summarised in TABLE 8-21. The first column in this table describes the regression equation being tested. Here C represents the regression intercept while ε represents the error term. The first row describes the model with only STRUCTURAL ROBUSTNESS as the predictor. Forward regression was performed to determine the best model. The second row describes the model with only KA as the predictor while the model in the third row uses both STRUCTURAL ROBUSTNESS and KA as predictors. The following are the observations:

a) In the IV sector, ASPL explains 22.9% of the variance in PV while KA explains 20% variance. Thus, STRUCTURAL ROBUSTNESS is a slightly better predictor of patent value than KA in this sector. KA and STRUCTURAL ROBUSTNESS together do not result in a statistically significant model for predicting PV in this sector.
b) In the TFP sector, KA and STRUCTURAL ROBUSTNESS together do not result in a statistically significant model. In this sector STRUCTURAL ROBUSTNESS is a better predictor *($R^2$=0.156)* of PV than KA *($R^2$=0.114)*.

c) In the PZ sector, STRUCTURAL ROBUSTNESS and KA explain 23% and 17% of the variance in PV, respectively. Together these two predictors improve the model by 20%. However, a higher standardized coefficient of KA *($B_{KA}$=0.413)* indicates that it is a stronger predictor.

d) In the CNT sector, robustness indicators RC and ASPL together explain the most variance in PV *($R^2$=0.565)*. Similar variance is observed when KA and NC are together used to predict PV *($R^2$=0.565)*. Robustness indicator RC singularly explains 23% of the variance in PV. Addition of KA to this model improves the prediction by 83%.

In all the sectors, STRUCTUAL ROBUSTNESS is a better predictor over KA when used singularly. Multiple predictors do not seem to improve the predictive power of the model in all the sectors. The interdisciplinarity of the sector may explain the regression results. The IV and TFP sectors are lower in interdisciplinarity *($HHI_{IV}$= 0.767, $HHI_{TFP}$=0.581)* compared to PZ and CNT sectors *($HHI_{PZ}$= 0.844, $HHI_{CNT}$=0.866)*. It is interesting to note that for low interdisciplinary sectors a single predictor (KA or STRUCTURAL ROBUSTNESS) provides a better prediction of PV whereas in highly interdisciplinary sectors an additional predictor variable further improves the model. The investigation into how interdisciplinarity affects patent value and its predictability is beyond the current scope of this research.

The models indicate that, all other variables held constant, a one standard deviation increase in knowledge accumulation boosts the technical value of an invention by 3%, 7%, 2% and 3% in sectors TFP, IV, PZ and CNT respectively. On the other hand, one standard deviation improvement in knowledge structure robustness increases the technical value by 5%, 8%, 8% and 7% in TFP, IV, PZ and CNT respectively.

**TABLE 8-21: Overall Model**

| Regression Equation Tested | TFP | IV | PZ | CNT |
|---|---|---|---|---|
| PV=C + ROB + ε | F(1,43)=7.936, $p<0.007$, $R^2$=0.156 | F(1,27)=8.017,$p<0.05$, R2=0.229 | F(1,51)=15.244, $p<0.001$, *$R^2$=0.23* | F(1,23)=7.232, $p<0.013$, *$R^2$=0.239*<br>PV=44.1+0.241(RC)+ ε |
| | PV=34.789+8.49 (ASPL) + ε | PV=23.057+16.894 (ASPL)+ ε | PV=15.76+22.02 (ASPL)+ ε | F(1,23)=14.3, $p<0.001$, *$R^2$=0.565*<br>PV=13.57+0.313(RC)+ 15.657(ASPL)+ ε |
| PV=C + KA + ε | F(1,43)=5.544, $p<0.023$, $R^2$=0.114 | F(1,25)=6.307, $p<0.05$, $R^2$=0.201 | F(1,51)=10.867, $p<0.002$, *$R^2$=0.176* | F(1,23)=6.233, $p<0.05$, *$R^2$=0.213* |
| | PV=46.53+19.83 (KA) + ε | PV=42.404+9.96 (KA)+ ε | PV=44.926+93.9 (KA)+ ε | PV=45.6+41 (KA)+ ε |
| PV=C + ROB + KA + ε | - | - | F(1,51)=9.568, $p<0.001$, *$R^2$=0.277* | F(1,23)=8.589, $p<0.002$, *$R^2$=0.438* |

| Regression Equation Tested | TFP | IV | PZ | CNT |
|---|---|---|---|---|
| | | | | PV=39.95+39.71 (KA)+0.23(RC) + ε |
| | | | PV=41.109+91.977 (KA)+0.116(NC)+ ε | F(1,23)=14.284, p<0.001, $R^2=0.565$ |
| | | | | PV=37.876+55.713 (KA)+0.22(NC) + ε |

Finally, I compare my model with the regression results presented in other studies. A comparison of the results indicates (TABLE 8-22) that KA and STRUCTURAL ROBUSTNESS explain at least the same amount of variance as other metrics and a higher $R^2$ value than some other studies. While it is not possible to compare the results directly with the other studies, because the dependent variables, predictors, and sectors differ, the results show that a satisfactory proportion of the variance in patent value can be predicted by knowledge accumulation and knowledge flow. Moreover, the KA and STRUCTURAL ROBUSTNESS indicators have the benefit of being leading indicators.

**TABLE 8-22: Comparison with other regression models**

| Sector | Study | Dependent Variable | Independent Variable | $R^2$ | Comments |
|---|---|---|---|---|---|
| Biotechnology | (Lin et al., 2007) | Citations | Examination Time, Claims, References, Dummy variables for inventor location | 0.14 to 0.36 | Citations reflect the value of invention |
| Manufacturing | (Hall et al., 2000) | Market Value of firm | R&D Stock, patent stock, citations | 0.16 to 0.25 | |
| Biotechnology | (Lerner, 1994) | Firm Valuation | Equity Index, number of patents, breadth of patent claims | 0.11 to 0.12 | Ordinary least square regression model used |
| Multiple sectors | (Harhoff et al., 2003) | Patent Value based on inventors' response to questionnaire | Patent scope, citations, family size, references, non-patent references, opposition, annulment | 0.12 to 0.17 | Ordered probit method used |

This research aimed to test the hypothesis that the characteristics displayed by the knowledge structure of inventions with high technical value are different from that of inventions of low technical value. More specifically two characteristics were further explored: knowledge accumulation and knowledge appropriation. It was hypothesized that the knowledge accumulation and knowledge appropriation observed in the knowledge structure of an invention are positively correlated with the technical value of the invention. The knowledge accumulation of an invention, as represented by the metric KA, indicates all the research efforts and knowledge that has had a direct or indirect effect in the creation of the invention. Knowledge appropriation as measured by STRUCTURAL ROBUSTNESS indicates the knowledge that has been absorbed in the creation of the invention. The parametric and non-parametric correlation tests performed in this research provide conclusive evidence that KA and STRUCTURAL ROBUSTNESS, positively correlate with technical value. Furthermore, collinearity diagnostics revealed that KA and STRUCTURAL ROBUSTNESS are new types of metrics and measure a different aspect of patent value that has not been captured by other existing indicators. Regression results show that the predictive power of these two indicators is better than some of the other metrics suggested in the literature. The knowledge structure of an invention evolves during its creation and crystallises when the technology matures. Since it does not change with time, it is an ideal source of information about technical value and can be used for the assessment of new inventions.

# 9 CONCLUSION

Technological maturity of an invention is an important contributor to its technical value. However, the quest to determine technological maturity is like the experiment of primordial soup[5]. We have some understanding of what its ingredients are. However, just bringing all the ingredients together doesn't necessarily create a life form. Some of the factors that contribute towards technological maturity have been identified. However, all these factors together are able to provide only partial answers to the question of technological maturity: What brings about the maturity of a technology? How does one know that a technology has reached maturity? This question is further complicated by the need of predictability. Can one foretell with accuracy, the technological maturity of inventions and therefore their value? Existing techniques either fail to produce a reliable assessment when the invention in question is new or depend on expert opinion that may be hard to come by.

Since technologies are made of bits and pieces of knowledge, it is fair to assume that the maturity of a technology must be some function of this knowledge. In that case, is age of the knowledge a determining factor? Is technology like wine, where the more it ages better is the output? If this were true, we would have witnessed more fuel cells in the market than OLEDs (organic light emitting diodes). The next potential candidate as an important factor could be the "quantity" of knowledge. This implies that the more one works on a problem the better are the chances of solving it. Intuitively this makes sense, though it doesn't explain why large-scale production of CNT (carbon nanotubes) is still not feasible despite exponential growth in research efforts. Or is the technological maturity simply a function of the capabilities of its creators? In this case a bigger group of inventors will always display collectively better capabilities than a lone inventor. However, many inventions result from single inventors. Due to such examples, the directionality of the relationship between technological maturity and its influencing factors seems unclear, which further complicates the predictability of technical value. These seemingly chaotic patterns of technologies beg us to look deeper for answers.

A potential answer to this question could lie in the knowledge structure of inventions. Knowledge structures emerge when existing knowledge elements are borrowed in order to solve the technical challenges in an invention. This knowledge structure grows until the technology of the invention is perfected. At which stage, the knowledge structure crystallises and does not change with time making it an ideal indicator to assess new inventions. At least two aspects of this knowledge structure may have an influence on the technical value of the invention: knowledge accumulation and knowledge

[5] The Primordial Soup Theory suggest that life on earth began in a pond or ocean as a result of the combination of chemicals from the atmosphere and some form of energy to make amino acids, the building blocks of proteins, which then evolved into the first species on Earth.

appropriation. The knowledge accumulation of an invention is indicative of the methods, procedures and efforts that have taken place to bring that specific invention into existence. This reveals the research efforts, both direct and indirect that have contributed towards the invention. The vast body of knowledge that shapes a technological sector is partially responsible for the technical viability of an invention. Hence, a higher knowledge accumulation should lead to a higher technical value of the invention. Knowledge appropriation describes the absorption of knowledge that has led to the creation of the invention. When an invention is based on an existing piece of knowledge, whether in the form of a prior invention or process, it indicates knowledge spillover. Knowledge spillovers are a result of active research and knowledge generation in the sector. In knowledge network spillovers appear in the form of citation links. A higher level of spillover creates more links that connect different parts of the network. The structural robustness of the knowledge network preceding an invention should represent knowledge appropriation within the invention.

Patent citation networks provide an ideal platform to represent the knowledge structure of inventions. Patent documents divulge unique legal and technical information about the invention. Patent-valuation analysis is a growing field that is increasingly finding applications in technology planning and management. The techniques have grown from mere patent counts to complex models. The references of a patent provide us information on the knowledge foundation of the invention. Tracing these references on multiple levels delivers a complete picture of the knowledge structure of the invention. I created co-classification based multiple-generation citation network to assess the knowledge structure of inventions. I adopted $G^s$ type of citation generation in forming the knowledge structures. Thus, the effect of each citation was accounted for exactly once.

My research aimed to test the hypothesis that the characteristics displayed by the knowledge structure of inventions with high technical value are different from that of inventions with low technical value. Two specific characteristics were explored: knowledge accumulation and knowledge appropriation. I further hypothesized that knowledge accumulation and knowledge appropriation displayed by the knowledge structure of an invention are positively correlated with the technical value of the invention. To test these hypotheses, I studied 152 inventions from four different sectors: Thin-film photovoltaics, inductive vibration energy harvesting, piezoelectric energy harvesting and carbon nanotubes. The major attributes of these sectors are that they are interdisciplinary and hold strategic economic and environmental importance. In order to study the knowledge structure of these inventions, I took into account the direct and indirect effect of all the knowledge elements that contributed to these inventions. Thus, effectively, this thesis analysed more than 4000 patents and examined their role in the creation of the target inventions. The technical value of these patents was calculated using patent indicators citations, references, family size and patent term. The use of such composite patent value has been well demonstrated in the literature.

This study identified a positive correlation between knowledge accumulation and the technical value of a patent thus, confirming the first hypothesis. A moderate effect size was observed in all the four sectors. It was observed that the sector is a significant predictor of the technical value only in IV sector. There was no observable multicollinearity between KA and other existing technology value indicators. A positive correlation was observed between KA-TII and KA-IMPORTB in TFP, PZ and CNT sectors. Also a negative correlation was observed between KA-TCT in PZ sector. No correlation was observed between KA and existing technical value indicators in IV sector. Since the metric does not strongly correlate or does not correlate at all with existing metrics, it is likely that the metric of knowledge accumulation is measuring a different construct. The measure of KA accounts for the complete knowledge base of an invention. As its measurement does not depend on forward citations, it is an ideal indicator for assessing newly granted patents.

Using the concept of network robustness, I found support for the second hypothesis. Structural indicators based on complex network analysis such as centrality, density, clustering, closure, etc. have been well studied in relation to knowledge flow within a knowledge network. However, the robustness of knowledge structures is an area that lacks active research. The robustness of a knowledge network indicates the degree of knowledge appropriation within an invention. In this thesis, the robustness of the knowledge structures was evaluated in three different ways: node connectivity (NC), robustness coefficient (RC), and average shortest path length (ASPL). RC and NC describe knowledge appropriation in terms of the connectivity within the knowledge network. Thus, an invention that is connected to a larger section of the knowledge elements has a higher probability of benefiting from that knowledge. ASPL describes knowledge appropriation in terms of the "distance" between the knowledge elements. A higher ASPL indicates that the knowledge has traversed multiple "hops" before reaching the invention. This may affect the efficiency of knowledge transfer therefore its appropriation within the invention. The results showed a positive correlation between patent value and all the three structural robustness indicators in TFP, PZ and CNT sectors. In the IV sector, only ASPL showed a statistically significant correlation with PV.  It was observed that relationship was stronger in samples from the CNT. The effect sizes of the correlation ranged from small to medium in TFP, IV and PZ sectors. While in the CNT sector the effect size ranged from medium to large. The results also imply that in all the sectors knowledge appropriation is enhanced when the knowledge elements are in close proximity thus, reducing loss of information.

Further investigation revealed that in all the sectors, STRUCTURAL ROBUSTNESS provided a better model over KA when used singularly. The use of multiple indictors yielded a statistically significant model in PZ and CNT sector. In the PZ sector, KA and STRUCTURAL ROBUSTNESS together explained 27% variance in patent value while in the CNT sector these indicators together explained 56% of the variance in patent value. Overall, improvements in knowledge accumulation and robustness on the technical value are more profound in IV sector. Finally, a comparison with other studies shows that the new model explains a higher amount of variance in patent value compared to most of the other studies.

The implications of this research show that the knowledge structure of an invention could reveal its technical value. Different characteristics of this knowledge structure, such as knowledge accumulation and knowledge appropriation, can be useful constructs by which to evaluate latest patents. Current patent valuation techniques based on forward citations or patent family fail to identify technically valuable inventions when the patent in question is new. Methods based on processing time can only be used on granted patents. The knowledge structure crystalizes at the inception of the invention and does not change with time. Therefore, the metrics described in this thesis can be used as a leading indicator of technical value of a patent. Research at pre-patent level can also be analysed similarly if sufficient information on the prior knowledge is available. From a technology management perspective, the identification of valuable inventions at an early stage would lead to better planning and execution of the invention. Inventions with no technical value will have no commercial value; thus, identifying such inventions at an early stage would save resources and time.

I contribute to this field of study by introducing the knowledge structural view of inventions in evaluating their technical value. The structural view attempts to find indicators of the structure inherent in the knowledge structure of an invention. This view attempts to disentangle the intrinsic structural effects at work in mediating the transformation of knowledge into practical products, i.e., innovation. My contribution therefore also includes the introduction of two new indicators of patent value: KA and STRUCTURAL ROBUSTNESS. In terms of advancing theory on technology forecasting, my research implies that every technology, even very complex ones such as energy harvesting and generation technologies, have some sort of underlying structure. The potential for improvement in those technologies due to their structures is relevant to questions of scientific interest in technology forecasting.

The methodological contributions of this research include techniques to measure knowledge accumulation in an invention and the application of the measure of network robustness in predicting the technical value of a patent. The robustness of patent citation networks has not been studied so far. The concept of knowledge accumulation, though used in assessing the technological developments of a sector (through TCL), has so far not been applied to individual inventions. The metric of knowledge accumulation takes into account the structure of the vast body of knowledge, experiences and research efforts that contribute specifically in shaping the invention. These two techniques are based on the knowledge structure of the invention, which is static and does not change with time.

It is vital for a technology manager or an investor to assess a technology from various angles in order to obtain a complete picture of its future performance. Such in-depth analysis should include both the “backward” and “forward” views. The forward view, as adopted by the current techniques, bases the value of an invention on the importance it holds for successive inventions. The backward view, on the contrary, looks at critical dependencies of the invention on prior technologies. These dependencies, unless thoroughly investigated, could lead to failure of the invention. For a technology forecaster, the techniques demonstrated in this thesis provide the backward view, which combined with the other current techniques, may give a better overall picture of the value of the invention.

The investigation into the differences in the characteristics of knowledge structures, as initiated in this thesis, has a vast scope for further research. First and foremost, it would be interesting to see how these characteristics change from sector to sector. From the results it appears that the interdisciplinarity of the technology may also contribute to how the knowledge structures pan out. However, a larger study involving technologies from a range of interdisciplinarity would reveal more information on the effect of interdisciplinarity on technical value.

Technology sectors also differ from each other in terms of their maturity and growth. Hence to gain further validity to the measures proposed in this research, the next steps should include investigation into more technological sectors that differ in terms of growth and maturity. Additional details could be added to the knowledge structure by including non-patent references. Such a knowledge structure would ideally include both journal articles and patents as knowledge elements and depict the transition from research to development. Future research could also proceed towards exploring additional features of the knowledge structure that may influence technical value.

Finally, I would like to point out certain omissions made in this study for the reason of simplification.

- In drawing the knowledge structures, I ignored the distinction made by other authors between inventor-references and examiner-references. The reason for this is that not every patent has these two types of references listed out separately. To maintain uniformity in the analysis, I included both the references.
- I excluded the non-patent references from the analysis in order to keep this analysis limited to patents at this stage.
- This study omits exogenous factors that may influence technical value.
- Some patents may share more than one IPC code with their references. This indicates a higher degree of similarity in the subject matter. However, I have included the references that share the key IPC only as this indicates that the inventions share the same core knowledge of the technology.

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