Modeling Technical Performance Change Using Design Fundamentals

by

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Doctor of Philosophy in Mechanical Engineering
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Abstract

Technical performance improvement exhibits exponential trends, but the rates of improvement for the 28 selected technological domains vary from 3 to 65%. Why does performance improve exponentially? Why do the improvement rates vary widely across the domains?

This thesis presents a simple theoretical model that provides an explanatory foundation based on two sets of well-known design fundamentals. The first set conceptualizes inventions arising through combinatorial analogical transfer where new operating ideas are created by combining operating ideas from an existing pool of ideas. This inventive process proceeds on a cumulative basis over time and is perpetuated by injection of basic operating ideas through synergistic exchange between science and technology. The combinatorial analogical transfer coupled with exchange between science and technology naturally leads to exponential behavior.

These operating ideas are then embedded in domain artifacts to improve technical performance. Interactions in artifacts and scaling of design variables - two domain specific effects from the second set of design fundamentals- modulate this process. Interactions in artifacts influence the ability of the domains to successfully assimilate the operating ideas. Assimilated ideas change design variables in the artifacts to improve their performance. The relative performance improvement depends on the scaling of design variables of the artifacts. Together these two domain parameters can potentially yield a wide variation in performance improvement rates. According to the model, higher domain interaction parameters retard, whereas higher scaling parameters accelerate, performance improvement rates. The model is shown to be consistent with what is known in the technical change literature.

An empirical study tests the model's prediction that higher domain interactions retard performance improvement rates of technological domains. A method for extracting domain interactions using a keyword-based text-mining approach on patents is presented. High normalized counts of keywords representing domain interactions are found to be negatively correlated with low performance improvement rates, thus supporting the model positively.

The thesis also presents an independent case study on performance improvement of permanent magnetic materials, and tests two regression models, which predict improvement rates using patent data. Performance of magnetic materials follows an exponential, but halting, improvement trend, and predicted rates from the regression models are consistent with prior result for the 28 technological domains.

Thesis Committee:

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To my mother and father,
Pam Kumari Basnet and Tara Bahadur Basnet
Who were untiring in their effort to have me, my brothers and sisters get the best education possible

And,
To my wife, Prativa Basnet and my daughter, Sasha Basnet
For their love and support, without which MIT would not have been possible.

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Acknowledgement

I came to MIT to pursue a PhD degree after 14 years in the industry after my MS degree, including more than 10 years at Bose Corporation as a mechanical design engineer. One major goal I had in mind for my PhD was to develop a broader perspective of design and technology. The last four years in Design and Invention Group (DIG) have been very fruitful achieving this goal and have stretched my mental muscles. I have often jokingly described my research with my friends as: I wanted to look at design from the top of a five-story building; I got more than what I wanted; I feel I am looking at design and technologies *from the clouds*. The research presented in this thesis afforded an opportunity to work with concepts and theories across economics, business and design science, and build on my industrial experience.

First and foremost I wish to thank my advisor, Christophe L. Magee. He was always accessible and actively engaged in my research. I thank him for mentoring and shaping my thinking on technological innovation. He supported not only by providing research assistantship over four years, but also by being patient in times of difficulty. Finally, he made it possible to visit Singapore University of Technology and Design (SUTD) twice, opening opportunities to build connections and friendships with researchers and scholars, and explore future opportunities. I also extend my thanks to SUTD-MIT International Design Center (IDC) for funding my research and providing me a friendly, and creative workplace to conduct my research.

I would like to thank my thesis committee members – Daniel Frey, Stephen Graves, Daniel Whitney, and Maria Yang – for serving on my committee for over two years and providing critical comments and suggestions from different perspectives, helping to make my research thorough and rigorous. I would also like to thank James McNerney, and Jessica Trancik for valuable discussion on component interactions (complexity). Additionally, I want to thank two graduate interns from ENSTA ParisTech, Guillaume Baldo, Mohamed Walid Gara, and Sylvan Tsai for their support in coding and conducting empirical study of interactions using patents, an important component of this research. I also want to thank J. Kim Vandiver for serving as my academic advisor, and guiding me in selection of courses aligned with my interest and the qualifying exams.

In my journey to earn a doctorate at MIT, several people have provided important contributions. I want to first thank Warren Seering for providing valuable guidance and connecting me with my advisor, Chris Magee, which opened the opportunity for my current research. I want to thank my professors from Manhattan College - Robert Kleckner, Zella Kahn-Jetter, and Graham Walker – and my manager at Bose Corporation, Mark Temple, for support and encouragement to pursue a PhD degree. I want to thank my friends in my lab Chris Benson, Hyunesok Park, and Han Fang for lively discussions in our marathon reading sessions of journal papers, and providing support and valuable feedback. Likewise, I want to thank my colleagues and friends at IDC and in MIT campus - Mark Jeunnette, James Penn, Lennon Rogers, Christina Morrison, Anna Young, Jose Gomez-Marquez, Chintan Vaishnav, Joa Castro, Martin Steinert for their support and friendship, I want to extend special thanks to my friends, Marty and Manish Deopura, for their enduring support and encouragement over many years from the time I contemplated pursuing a PhD degree to this day.

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Chapter 1: Introduction

1.1 Introduction

Improved understanding of technological change dynamics can help corporations, who design and manufacture engineering products and services, private and public investors, economists and policy makers (Solow 1956, Arrow 1962, Meyers 1969, Utterback 1974, Dosi 1982, Rosenberg 1982, Musson 1989, Henderson and Clark 1990, Girifalco 1991, Klevorick et al. 1995, Christensen 1996, Langrish et al. 1997, Ruttan 2001, Lipsey et al. 2005, Baldwin and Clark 2006, Koh and Magee 2006, 2008, Luo et al. 2012, Magee et al. 2014, Benson and Magee 2015b). Products are often designed using sub-systems based on different technologies. The technological performance existing at a particular point of time for complementary technologies strongly influences when a specific concept is actually ready for the market. An example of such a situation has been discussed by Kurzweil (2005) concerning the readiness of reading machines for the blind which had to await developments of computation in the early 21st century to become realistic. This illustrates the importance of being able to forecast rates at which performance of different technologies improve so that engineering management can plan and strategize their technological roadmap and private and public investors can make better judgments about investment in specific technological ideas. A notable example of lack of understanding of dynamics of technological improvement which resulted in heavy financial losses in clean technology[1] is summarized by Fehrenbacker (2012):

> *"... one of the key misplaced assumptions that VCs made in the cleantech boom times is that the rapid progress of Moore's Law ... could be created for cleantech with a little bit of VC funding and Silicon Valley smarts. The notion (which is seductive but not true in most cases) is that the traditional energy industries throughout the world just didn't*

[1] 'Clean technology (clean tech) refers to products, processes, and services that delivers value using zero or limited non-renewable resources and/or creates significantly less waste than conventional offerings.' Clean technology includes products such as solar power systems, hybrid electric vehicles, and water filtration. Pernick and Wilder (2008 pp 2)

do the right kind of innovation and that the Valley's can-do spirit and open wallets would be able to unleash this potential."

These examples clearly point to the practical need: 1) to have an empirical understanding of how different technologies improve; 2) to have theoretical understanding of underlying dynamics that drives improvement of technologies and potential factors that determine their rates; 3) to develop better ways to judge technologies' potential for improvement, perhaps even to discover new approaches that enables faster improvement.

1.2 Motivation of current research

Technological change has generally been studied by business scholars and economists who have provided valuable insights regarding how technologies improve and how they diffuse (Griliches 1957, Fisher 1971, Grubler 1991, Pistorius and Utterback 1997, Comin and Mestieri 2013). Most of these scholars, however, have viewed technical change as occurring inside a black box, and have treated inventive design processes, the source of (fundamental mechanisms underlying) technological change, as exogenous or unimportant. As a consequence, no model, to our knowledge, exists that connects the external technological behavior with the underlying mechanisms of design and invention, including the role of science. The work reported here is motivated by the desire to complement prior research and enhance theoretical understanding of technological change by incorporating the insights of design and invention processes.

1.3 Problem Statement

Within the large and complex field of technical change, the current research specifically concerns itself with empirically observed performance trends - exponential improvement of technological performance and wide variation of their rates across the domains (Moore 1965, Martino 1970, Girifalco 1991, Koh and Magee 2006, 2008, Nordhaus 2007, Magee et al. 2014). To understand this observed phenomenon, several areas of research have been identified, of which we here discuss the first. To improve consistency and reduce ambiguity in measurement of technology performance and its improvement, our research group (which includes the current author) have chosen technological domains as the unit of analysis. In our formulation, technological domains consist of a set of designed artifacts that utilize a recognized body of knowledge to achieve a specific generic function (Magee et. al. 2014). The artifacts considered can be products, software, or processes. The body of knowledge is principally scientific and engineering knowledge. Nine categories of functions, such as energy storage, energy transport, information storage, information transport, are considered. Each functional category is decomposed into technological domain based on the scientific knowledge utilized by artifacts considered. The available data has been, accordingly, adapted to construct performance data for 28 domains (Magee et al. 2014). The performance metric of a technological domain, defined from the perspective of users of technology, is a composite indicator which includes essential functional outputs and a resource constraint (e.g., cost, volume or mass of the artifact) important to the users. The performance metric is formulated such that higher performance is considered better by the users, and expressed per unit of resource considered. The performance normalized with respect to a resource is referred in this thesis as an intensive performance[2] whereas the non-normalized performance is referred as an extensive performance. The analysis has demonstrated that intensive performance for the 28 technological domains considered in this thesis improve exponentially, but the annual improvement rates vary widely ranging from 3 to 65 percent.

Two important research questions have emerged from these observations and are the focus of this thesis: Why does the technological performance grow exponentially? Why do they grow at widely varying rates? In the current study, we address the two questions theoretically. In particular, we examine *performance trends* - the time dependence of performance as realized in *a series of improved designs* of artifacts that arise over time. Towards this end, we have brought together three bodies of research that do not usually interact. The first is the design research field, particularly its cognitive scientific insights on the design process. The second is the technological change field where most researchers

[2]It has to be noted that some literature define intensive properties as being independent of size of the artifact. This interpretation is not applicable to interpretation of intensive performance as formulated in this thesis.

have been economists or business scholars. The third area is quantitative modeling of performance of artifacts. We have constructed a simple explanatory mathematical model (supported by simulation) founded on important features of the invention and design process – combinatorial analogical transfer, interactions, and scaling. The model also utilizes the synergistic exchange between science and technology. In a complementary study, Benson and Magee (2015b) have examined prediction of the performance improvement rates using patent meta-characteristics. They did so empirically (and successfully), but did not address why the trends are exponential and why the rates vary.

A further research task accomplished in this thesis has been to test the mathematical model by conducting empirical studies of domain interactions. In addition, performance improvement of permanent magnetic materials has been studied as a case study to test two predictive regression models based on bibliographic data and textual content in patents.

1.4 Thesis structure

This thesis is divided into five chapters. Chapter 2 reviews related literature in four broad areas: technological change, design science research, modeling methods, and patents and their analysis. Section 2.1 examines salient literature on why and how technological change occurs. In particular, it examines the literature on empirically observed performance trends and wide variation in rates. Section 2.2 provides an overview of three areas in the design science literature. The first area is the combinatorial analogical transfer as related to inventive and design processes. This includes taxonomy of knowledge, and concepts related to the relationship between science and technology. The other two topics discussed in section 2.2 are domain interactions and scaling.

Section 2.3 reviews prior work on quantitative modeling of technological change. Specifically, it looks at the work of Muth (1986) based on random search, of Axtell (2013) on agent-based modeling, and that of Arthur and Polak (2006) on simulation-based studies. The final section 2.4 reviews literature on patents and their analysis. Specifically, it focuses on the classification overlap method (COM) which is important to the work in this thesis on domain interactions, the permanent magnetic materials case study, and analysis techniques for patent content.

Chapter 3 presents three sets of results with methodology. Section 3.1 begins with a qualitative description of the structure of the model, followed by a progressive development of the mathematical model incorporating simulation-based results, interaction and scaling parameters. Section 3.2 presents results from an empirical study using patent content, which tests the interaction parameter identified by the model. Section 3.3 provides results from a case study of performance of permanent magnet materials used for testing predictive regression models.

Chapter 4 is the discussion of the empirical results and the mathematical model. The results from the case study of permanent magnet materials are first discussed in section 4.1. Section 4.2 enumerates the assumptions in the model and examines their testability, while section 4.3 discusses assumptions and limitations in the empirical studies. Section 4.4 discusses the implications of the model and empirical work, and section 4.5 reflects on the modeling work.

Chapter 5, the concluding chapter, discusses the contributions and the questions spawned by the research effort, including extension of the model to study improvement of technological capacities in smaller units of analysis such as organizations, and countries.

Please note that the figures, tables and equations are numbered chapter-wise.

1.5 Acronyms and nomenclature

The frequently used acronyms and mathematical symbols are summarized below.

COM = Classification Overlap Method: The method used in this thesis to select relevant and complete sets of patents to represent a technological domain.

Q_J = intensive performance of a technological domain, J

t = time; t_0 = time at t = 0

IOI = individual operating ideas

P_{IOI} = probability of combination of any two IOI

IOI_0 = basic IOI - IOI that first introduce a natural phenomenon in the operations regime

IOI_C = cumulative number of IOI in the operations regime

IOI_S = IOI successfully integrated into a domain artifact

K_I = annual rate of increase in IOI_c in the Operations regime

K_J = annual rate (when time is in years) of performance improvement measured by the slope of a plot of lnQ_J vs. t (regression coefficient)

F_U = cumulative fitness of Understanding regime

d_J = interaction parameter of domain J defined as interactive out-links from a typical component in domain J

s_J = design parameter affecting the performance of an artifact in domain J

A_J = exponent of design parameter in power law for domain J, relating it to performance

Chapter 2: Review of Prior Literature

This chapter provides an overview of existing literature in four broad areas related to improvement of technology. The first three - technological change, design science, and quantitative modeling - are essential for developing the mathematical model. The fourth - patents and related analytical techniques - provides the background for the empirical study of interaction and for the case study.

2.1 Technological change literature

Within the field of technological change, three areas of research are pertinent to our questions concerning trends in performance improvement. The first two are concerned with answering why technological improvements occur and what the structure of technical improvements is. The third one focuses on quantitative measurement and analysis of technological performance.

2.1.1 Economic effects and technological change

What descriptive models and theories help us understand why technologies improve? Schumpeter (1934) introduced the idea that entrepreneurs, whose primary role is to provide improved products and services through innovation, drive economic progress. These innovations, which Schumpeter describes as industrial mutations, displace competing products and services from the economy. However, they, too, are displaced by higher performing innovations that follow, thus perpetuating the cycle of creative destruction.

Building upon Schumpeter's notion, Solow (1956) recognized and incorporated technological change as the key element in his quantitative explanatory theory of economic growth. Approaching technological change from an economic perspective, he modeled growth in GDP, G, as an aggregate production function: $G = A(t) \cdot f(K,L)$, where K, and L are capital and labor inputs in physical units, and $A(t)$ represents the accumulated shift in the production function due to technological change over a period of time t. Applying his model to GNP data for the US from 1901 to 1949, and assuming the value of $A(t)$ in 1901 to be 1, he calculated the value of $A(t)$ in 1949 to be to 1.89. In other words, the accumulated technological shift had altered the nature of effective production function such that GNP was 1.89 higher for the same level of labor and capital inputs. The basic conclusion of Solow that technological change is the foundation of sustained economic growth has stood the test of time. Later theorists of economic growth (Arrow 1962, Romer 1990, Acemoglou 2002) have attempted to deal with the more complex problem of embedding technological change within the economy (endogenous to different degrees).

Although this is important work, it is outside the scope of this research and will not be covered further here. A related question of sources of innovation does have more relevance.

2.1.2 Sources of technological change

What are the drivers of technological innovation? The technology change literature has broadly classified the drivers of innovations into demand-pull and technology-push. Some early explanations emphasized pure demand pull (Carter and Williams (1957, 1959), Baker et al. 1967, Myers and Marquis 1969, Langrish et al. 1972, Utterback 1974) where the needs of the economy at a given time dictate technological direction. Amongst these studies, study of Myers and Marquis (1969) is frequently cited, and perhaps the most important in emphasizing the role played by demand. Myers and Marquis conducted an empirical study of 567 innovations (designs and sources of information for subsequent innovations) in five industries - railroads, railroad-equipment suppliers, housing suppliers, computer manufactures, and computers, and computer peripheral suppliers - with a goal to develop an empirical insight about factors that spur the application of scientific and technological findings in the civilian economy. Their finding was that recognition of a demand was a more frequent factor in innovation than recognition of a technical potential. Baker et al. (1967 and 1971) were, on other hand, concerned with idea generation in an industrial setting. As silent observers and note-takers they studied corporate research lab's ideation activities and analyzed the ideas generated. In one analysis they classified the ideas generated based on the type of 'stimulating events'. The 'needs event', were defined as 'recognition of an organizational need, problem or opportunity", and 94 percent of ideas were classified under this category. In "means events," defined as "recognition of a means or technique by which to satisfy the need, solve the problem, or capitalize on the opportunity", 92 percent of ideas were classified. Overall, they concluded that 75% of ideas and 85 % of those subjectively rated as the best ideas, were classified as arising from "need-means" sequence, alluding to the role of need in innovation but also the role of means or technological solutions. The primacy of demand-pull was emphasized in a review article in *Science* by Utterback (1974), who summarized his empirical finding as follows:

> *"Market factors appear to be the primary influence on innovation. From 60 to 80 percent of important innovations in a large number of fields have been in response to market demands and needs. The remainder have originated in response to new scientific or technological advances and opportunities. There is a striking similarity between the studies conducted in the United States and those conducted in the United Kingdom [pp 621]".*

Mowery and Rosenberg (1979) were very critical of the findings published in support of demand-pull as the primary force for innovation. They note that these studies are "seriously flawed and, in many cases, invalid". Out of many reasons, one they emphasize is: The notion of need used in these studies is much looser than the concept of demand in economics, which has a 'more restrictive and precise definition". This issue has led to an identification problem: "Is an innovation introduced because the demand for a product has increased (i.e. the demand curve has shifted outward) or because technological improvement (or other sources of cost reduction) now make it possible to sell the product at a lower price. The first case is the one required to support the "demand-pull" hypothesis."

Mowery and Rosenberg have reanalyzed the data and methodology in these early works and arrived at an equally strong role for science/technology push (the discoveries of scientists and inventors primarily determine technological direction) in spurring innovations. Instead of saying only demand-pull or technology push is important, they have highlighted that "both demand and supply-side influences are crucial to understanding the innovation process". In fact, "...any careful study of the history of an innovation is likely to reveal a *characteristically iterative process, in which both demand and supply forces have responded"* (emphasis mine) and "innovations which are not highly sensitive to both sets of forces are most unlikely to achieve the status of commercial success."

Taking a balanced view similar to that of Mowery and Rosenberg, Dosi (1982) has also advocated that both market-pull (customer needs and potential for profitability) and technology-push (in the form of promising new technology, and the underpinning procedures) are equally important for being sources of innovation. He has also pointed that there is a complex structure of feedbacks between economic environment and the directions of technological change. Although impressionistic, in the same paper, Dosi has furthermore shed light on the nature of technological change with his suggestion that we can conceptually view technological change occurring as a series of technological paradigms and technological trajectories (both concepts are highly cited). Borrowing from the analogy to scientific paradigms as described by Kuhn (1962), Dosi defines technological paradigms as an outlook, a set of procedures, a definition of the relevant problems, and of the specific knowledge related to their solution". A trajectory is a directional advance within an area circumscribed by a paradigm.

A recent finding on changes in preference structures as triggers of innovation (Tripsas 2008) has added a new dimension to demand-pull. In previous studies of demand-pull and technology-push, Tripsas notes, customer preferences were considered static. She has shown, using the case study of evolution of typesetter industry, that changes in customer preferences are a reality and they act as an economic feedback, as mentioned by Dosi(1982), to set in motion significant innovative efforts. Some salient examples of drivers of significant changes in preference structures are: a) shifts in government regulation (pollution control), political change (opening of borders in Eastern Europe), and evolution of customer needs (insurance companies requiring better computers for data processing). However, Mowery and Rosenberg's point still stands since the preference changes covered by Tripsas were made possible by the technological changes she studied and she does not show increasing demand before the technological change occurred but in most cases, the need or demand was long-standing.

2.1.3 Theories on structure of technological change

What patterns does technological change exhibit? Several models have been developed to answer this question from different angles, which will be discussed sequentially.

S-curve theory: This concept has been widely used by technology strategists. Sahal (1981), Utterback (1974), and Foster (1986), have been the main supporters of this view. According to this theory, technological performance exhibits a nature of an S-curve (see figure 2.1). It is explained that this trend actually is a result of three stages: introductory, growth, and maturity. During the growth stage, performance of a technology grows slowly (early part of the S-curve) since the firms may have to spend effort to set up, understand the problem and overcome bottlenecks. As a result, change in performance is meager during this stage. In the growth period (the middle phase of S-curve), with continued research effort, the technology passes a threshold value and makes rapid progress. This period sees rise of a dominant design around which consumer preferences coalesce (Utterback 1974). In a maturity phase (last part of S-curve), the rapid improvement of performance transitions to a slower pace. Many reasons have been proposed for this maturity of the technology. Foster (1986) suggests that maturation is an innate feature of innovation, implying the notion of a limit. Utterback (1994), and Adner and Levinthal (2002) suggest that as a market ages, the focus of innovation shifts from the products to process, leading to reduced increase in performance.[3]

[3] In their definition of performance of a technology, Magee et al (2014) include cost as one of the resource constraints that determines performance of a technology. According to this definition, process improvement leading to reduction in cost results in performance improvement.

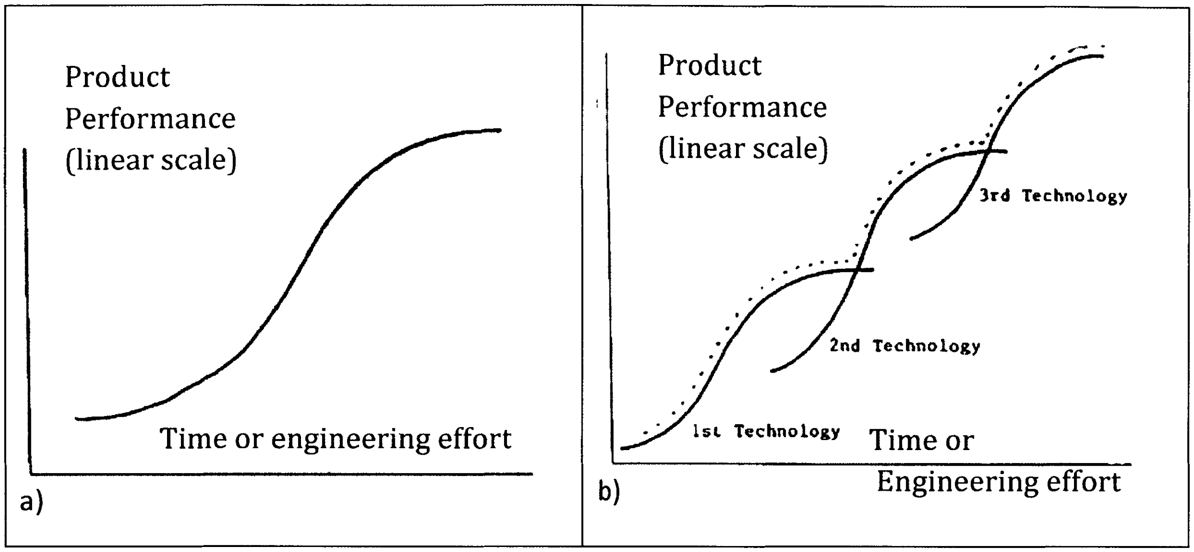


Fig 2.1: Technology S-curves a) single b) multiple

Christensen (1992), a scholar of technology strategy, states that "The technology S-curve has become a centerpiece in thinking about technology strategy." He has utilized this concept to build his theory of disruptive innovation (which will be discussed shortly). Although the S curve theory is fairly widely accepted, it contains some large flaws. First, there is no data in any of the papers discussing it that shows statistically acceptable deviations from an exponential (hints of bending over are generally reversed if further data is obtained). Second, all data on R&D indicate that product R&D continues to totally dominate process R&D even in fairly old industries such as the electrical power production, the automotive and appliance industries where product spending is perhaps at least an order of magnitude greater than process R&D even today. Besides being empirically vacuous, S curve theory has conceptual challenges including non-operational definitions of "dominant design" and apparent confusion between diffusion (which has long been shown to empirically-and theoretically- to follow an S curve) changes with time vs. performance changes with time. In a recent study on theories and hypotheses and empirical data on S-curves, Tellis and Sood (2005) failed to find 'any single, strong, and unified theory for the S curve', and found only scattered empirical to support it. Indeed, Christensen's own work does not show S curves despite his apparent endorsement of it. Some have hypothesized that apparent exponentials may be a series of s-curves. Statement that they are still exponential overall is not a testable hypothesis but may be correct (and not inconsistent with the model developed in this thesis).

Incremental versus discontinuous change: The notion that technological change occurs as a series of incremental change punctuated by discontinuities (large changes) is a popular view among scholars (Hill and Utterback 1980, Tushman and Anderson 1986, Bourgeois and Eisenhardt 1988, Henderson and Clark 1990, Hoisl et al. 2014). Using data from the minicomputer, cement, and airline industries from their births through 1980, Tushman and Anderson (1986) have indicated that technology improvement evolves as a series of incremental changes punctuated by discontinuities. Figure 2.2 shows performance (seat-miles-per-year capacity) of most capable airplanes flown by US airlines, where instances of large percentage change represent discontinuities. These discontinuities, they argue, have large socio-technical effects, but are an essential element of technological change. They can come in the form of competence-destroying initiated by new firms, or in the form of competence-sustaining initiated by existing firms. We should note that the airplane data below misses some points found in the more extensive work of airplane performance reported by Martino (1971), and that Martino shows that overall the long-term performance increases exponentially.

In another highly referenced paper, Henderson and Clark (1990) state that modeling technological change as incremental and discontinuous change in performance is incomplete, and cannot explain industrial cases where large incumbent firms were overwhelmed by seemingly innocuous products from entering firms. Xerox lost half of its share to small copier manufactures, and RCA lost its shares to Sony's portable transistorized radio. In both of these cases, it was not a discontinuity in performance related to some significant scientific breakthrough that caused this turbulence. Instead, it was the importance of architectural change of artifacts - as opposed to component change - having large effects on the firm level impact of change.

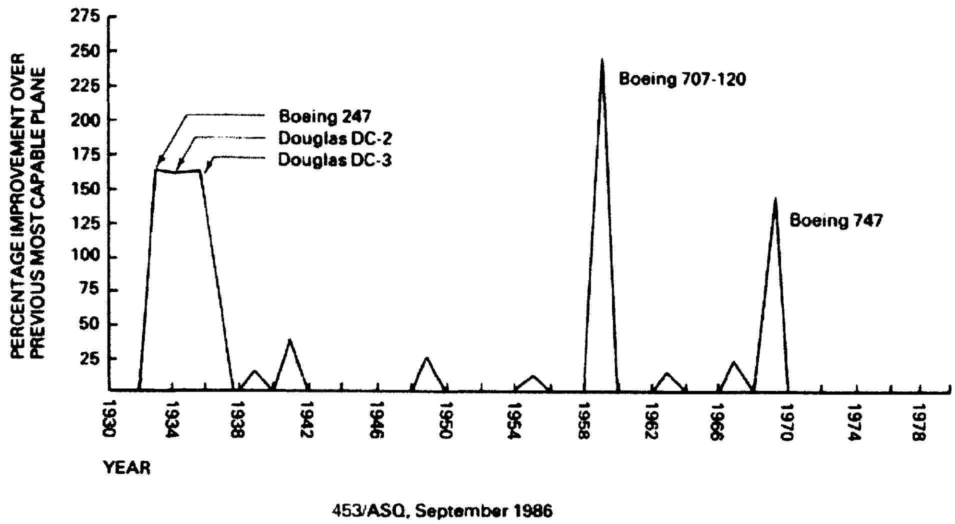


Fig. 2.2: Discontinuities in performance of airplanes (Seat-miles-per-year capacity of most capable airplanes flown by US airline 1930-1978). Adapted from Tushman and Anderson 1986.

Christensen (1996), on the other hand, views technological change occurring as a series of disruptive product innovations. As mentioned earlier, he builds his model of disruptive innovations using the concept of S-curves. Christensen describes a disruptive technology as starting in a niche market (see right plot in Fig. 2.3) with a different set of functional requirements using a novel architecture, but lags behind with respect to mainstream performance (he uses extensive rather than intensive performance) in conventional markets (left plot in Fig. 2.3). Rapidly improving towards the requirements of mainstream performance, the disruptive technology surpasses the mature market leaders (by achieving the necessary performance in smaller, cheaper artifacts), and displaces them (left plot in Fig. 2.3).

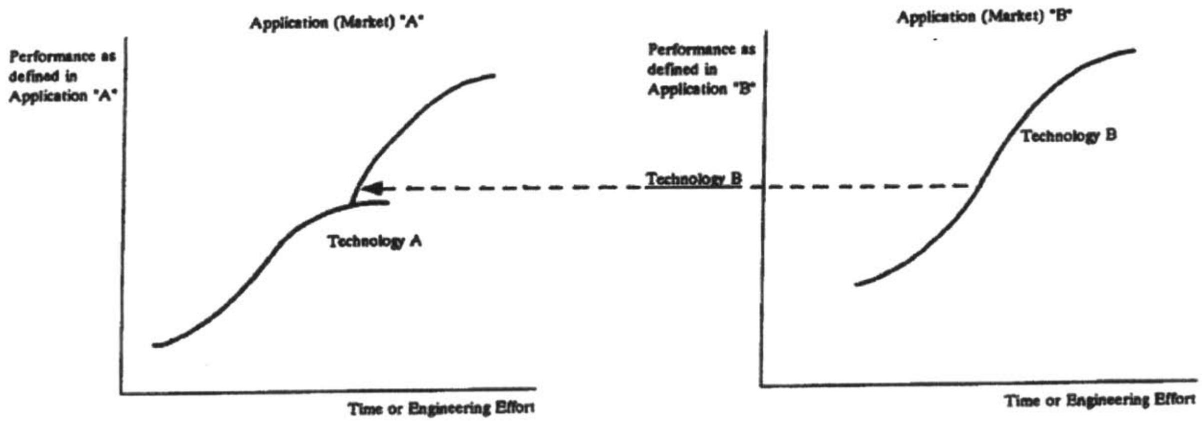


Fig. 2.3: A S-curve model of architectural innovation. Adapted from Christensen 1992b.

2.1.4 Technological performance change

All of the concepts of technological change described in the preceding sections, at least implicitly, depend upon relative rates of change of performance. This is the focus of our research so we will now briefly review concepts related to trends in performance of designed artifacts, and what patterns they have followed. We first review two established frameworks – generalizations of Wright's early research, and Moore's Law - for describing trends in technological performance. The difference between the two approaches lies in the use of the independent variable: Wright's approach uses cumulative production, whereas Moore's approach uses time.

2.1.4.1 Wright's Approach

In 1936, Theodore Paul Wright (1936) in his seminal paper "Factors affecting the Cost of Airplanes" for the first time introduced the idea of measuring technological progress of artifacts. From his empirical study of airplane manufacturing, he demonstrated that labor cost or total cost of specific airplane designs decreased as a power law against their cumulative production. Fig. 2.4a shows the reduction of cost (labor and total) decreasing as a straight line in log-log graph. This relationship is expressed mathematically as:

$$C = C_0 P^{-w} \tag{2.1}$$

Where C_0, and C are unit cost of the first, and subsequent airplanes respectively, and where P and w are cumulative production and its exponent that relates it to unit cost; it is now sometimes called Wright's Law (by analogy with Moore's Law - see below). Wright explains that labor cost reductions are realized as shop floor personnel gain experience with the manufacturing processes and material usage, and have access to better production tools. It should be noted that Wright did not look at improvement due to new designs (which is the focus of our work). Rather he looked at cost reduction of specific aircraft designs due to improvements made on the factory floor. Each curve in Fig. 2.4b plots the unit cost of individual airplanes for different designs as a percent of the total cost of the series plane produced as a function of total numbers of airplanes manufactured.

Since Wright's work, this approach has been used to study production of airplanes and ships during World War II, and extended to private enterprises (Yelle, 2007).

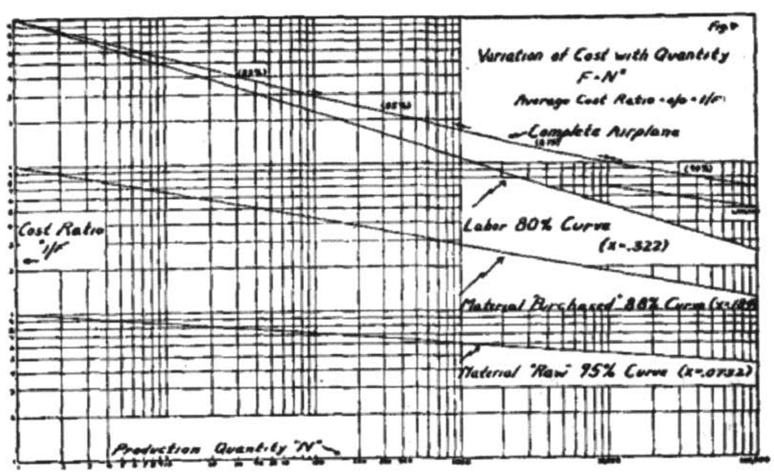


Fig. 2.4 a: Reduction in unit cost as a power-law of cumulative production. Adapted from Wright 1936.

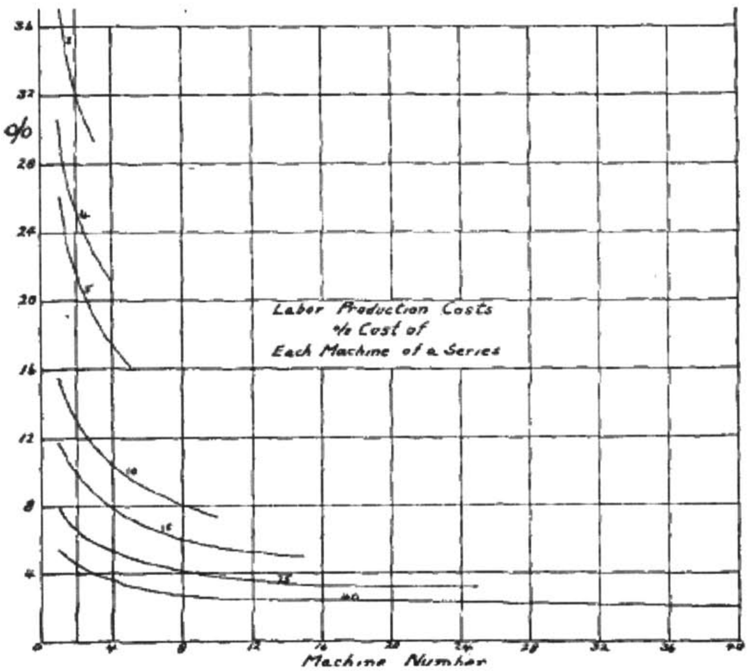


Fig. 2.4 b: Reduction in unit cost as a function of cumulative production. Each curve represents a separate design. The cost of each machine plotted in a percent of total cost of each series for varying quantities. Adapted from Wright 1936.

2.1.4.2 Moore's Approach

Gordon Moore (1965) presented the second approach - using time as the independent variable - in his seminal paper that describes improvement in manufacture of integrated circuits. He observed that the number of transistors on a die was doubling roughly every 18 months (modified to 2 years in 1975). Fig. 2.5a shows improvement in the number of components in dies utilized for memory and processors. This exponential relationship between the number of transistors on a die and time, famously known[4] as Moore's Law, can be mathematically expressed as:

$$Q_J(t) = Q_J(t_0)\ exp\{K_J\ (t-t_0)\} \qquad (2.2)$$

[4] This designation was given to the relationship by California Institute of Technology professor Carver Mead.

Where $Q_J(t_0)$ and $Q_J(t)$ are the number of transistors per die (a measure of performance) at time t_0 and time t, and K_J is the rate of improvement (annual if time is in years). For integrated circuits, the exponential relationship has held broadly true for five decades.

In a recent paper, Moore (2006) has summarized the explanatory factors that are responsible for the rapid improvement in the density of transistors in Integrated Circuits. Fig. 2.5b summarizes three factors - improvements in die size, reduction in feature dimensions, and device and circuit cleverness - that have contributed towards improvement in the number of components in the chip. One important point to note is that all three are growing exponentially. Moore says the third factor, which includes ability of engineers to minimize wasted space, and isolation structures, was exhausted in about 1975, leaving the other two as most important contributing factors.

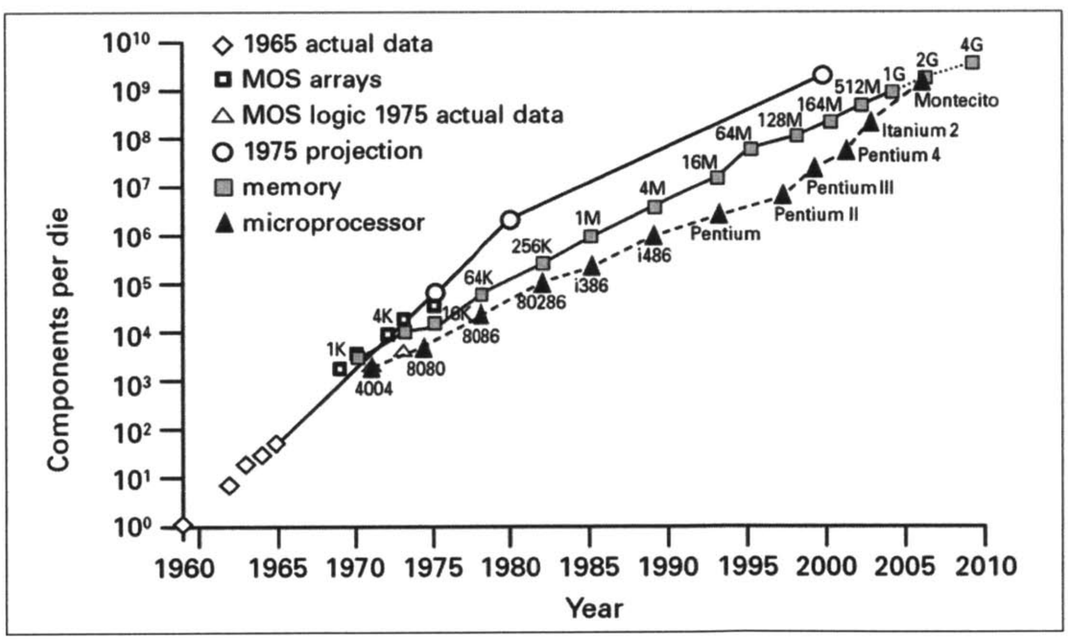


Fig. 2.5 a: Improvement in the number of components per semiconductors die. Adapted from Moore 2006.

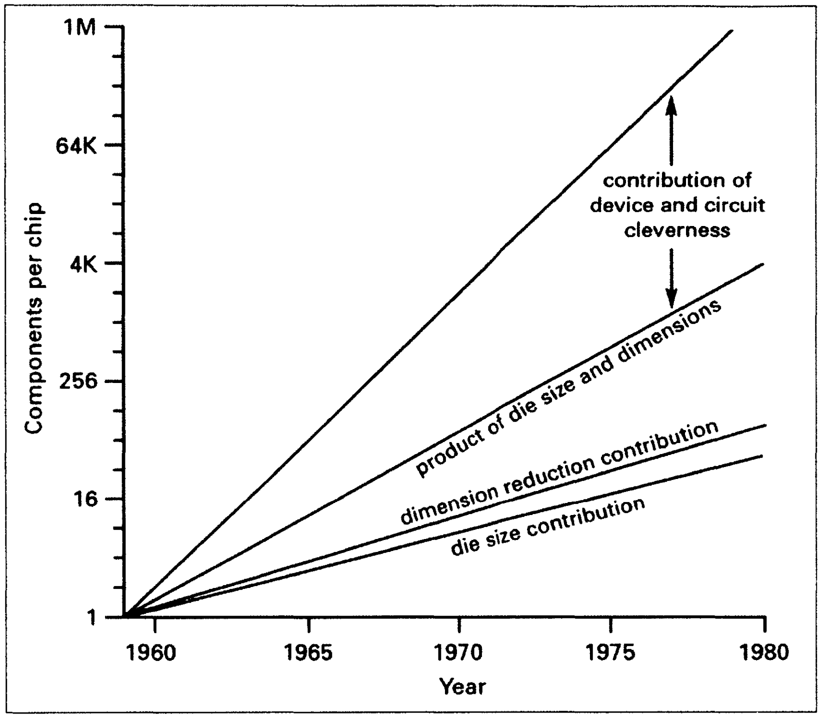


Fig. 2.5 b: Factors contributing towards improvement in number of components per die. Adapted from Moore 2006.

Others (Martino 1971, Girifalco 1991, Nordhaus 1996, Koh and Magee (2006, 2008) and Leinhard 2008) utilized this temporal approach to study performance of different technologies, and have demonstrated that many technologies exhibit exponential behavior with time. More recently, Magee et al. (2014), discussed in more detail shortly, extended the study to 73 different performance metrics in 28 different technology domains. The performance curves have continued to demonstrate exponential behavior, although annual rates vary widely across domains.

We note that Moore and all others who used his framework basically compared the performance of different designs over time differentiating the Wright and Moore frameworks. However, it is also possible to use the Wright framework for different designs but only if the amount produced increases exponentially with time (Sahal 1979, Nagy et al. 2013, Magee et al. 2014). We discuss the relationship between the two approaches next.

2.1.4.3 Equivalence of Moore's and Wright's approaches

In his paper, *A Theory of Progress Functions*, Sahal (1979) first noted that exponential trend in performance for a technology can be obtained from Wright's power law if the cumulative production of that technology is also growing exponentially. This equivalence can be viewed as a decomposition of Moore's Law (K, slope of the curve) into a product of Wright's exponent (w, slope of power law) and the time derivative of the logarithm of production (g, slope of log production vs. time curve). Mathematically, this is:

$$d \ln Q_J/dt = d \ln Q_J/d \ln E_J \cdot d \ln E_J/dt \qquad (2.3a)$$

Where Q_J and E_J are performance and volume of production (or effort) of a technology J at time t.

Since each term is a constant, the equation can be rewritten as:

$$K = w.\, g; \qquad (2.3b)$$

$$w = K/g \qquad (2.3c)$$

Where,

$$K = d \ln Q_J/dt \qquad (2.3d)$$

$$w = d \ln Q_J/d \ln E_J \qquad (2.3e)$$

$$g = d \ln E_J/dt \qquad (2.3f)$$

In a statistical study of 62 different technologies, Nagy et al. (2013) examine predictive capabilities of these two models, and their relationships with each other. They show that production of many technologies grows exponentially with time, with variable quality of the exponential fit. Fig. 2.6 on page 40, for example, shows exponential growth in production for PVC, as well as for exponential reduction in unit cost (e. g., US$/lb). They have tested the equality in equation 2.3c by comparing values of w, the exponent of Wright's power law, with the ratio of K (exponent from Moore's law) and g (exponent of production growth), see Fig. 2.7. The reliability of equation 2.3c, demonstrated by proximity of all the points on the line of equality, is surprisingly good.

The annual or cumulative production is a measure of an effort variable. In a more recent article, Magee et al. (2014) following Foster, Christenson and others note that other potential effort variables are revenue, profit and patents in a technological domain. Using production, revenue, and patent data for IC chips as different measures of effort, they have shown that, in each case, the relationship in equation 2.3a holds. Table 2.1 presents the empirical values of w and g for each effort variable, with value of R^2 in parentheses. It is clear that the calculated K values (column 3) using three different effort variables are very close to the empirically obtained K value (inside parenthesis in column 3), supporting the idea the patents, production, and revenue are a useful measures of effort.

Magee et al. (2014) argue that, although both approaches may be used, Moore's approach is preferable. This is because, Wright's approach requires both performance and production data whereas Moore's requires only performance data. Production data is hard to reliably obtain, especially at the technological domain or industry level. Furthermore, if cumulative production is used as an effort variable, lack of production, especially data early on, introduces serious distortion to the trend. For this reason and one other, they recommend using Moore's approach to study the performance improvement. The second reason is that with patent data for 28 domains they show that Moore's Law is followed even when patents do not increase exponentially with time but Wright's relationship is only followed reliably when patents do increase exponentially[5]. The work of Magee et al. provides the empirical foundation for the theoretical work presented in this thesis, so it is discussed in detail next.

[5] See Fig. 5 – and Fig. 4 – working paper by Magee et al. (2014).

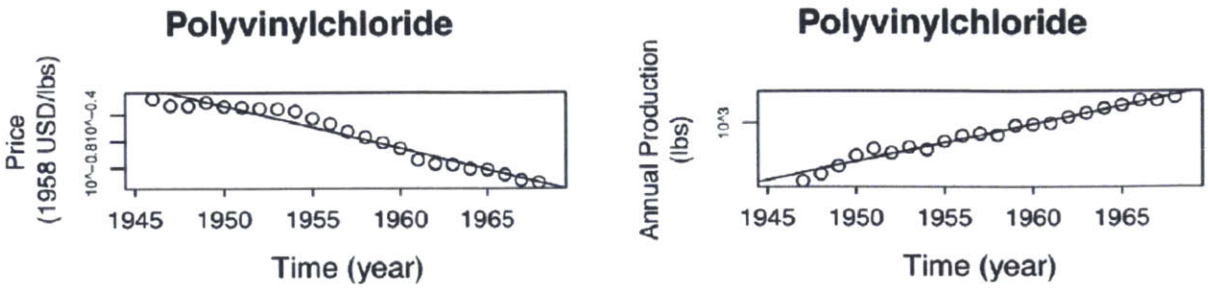
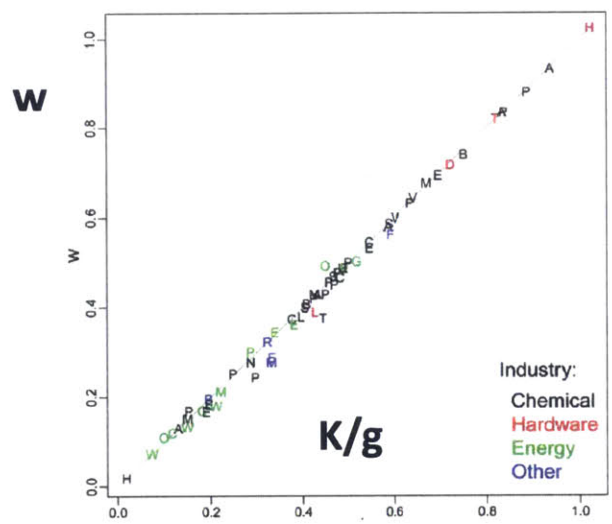


Fig. 2.6: Unit price and production varying exponentially. Adapted from Nagy et al. 2013.



w = slope from log-log graph of unit cost versus production

K = slope from log-linear graph of unit cost versus time

g = slope from log-linear graph of production

Fig. 2.7: Equivalence of Moore Law and Wright's relationship. Adapted from Nagy et al. 2013.

Table 2.1: Empirical values of g and w for IC processors with the dependent variable (Q) = transistors/die. The empirical value of K for this dependent variable is 0.36 in good agreement with the values estimated from Sahal's relationship ($K = g \cdot w$). Adapted from Magee et al. (2014).

Independent effort-variable	**g from equation 2.3f and (R^2)**	**w from equation 2.3e and (R^2)**	**Estimated $K = w \cdot g$ {empirically det. K}**
Production/demand	0.59 (.97)	0.6 (.99)	0.35; {0.36}
Revenue	0.095 (.91)	3.4 (.88)	0.32; {0.36}
Number of Patents	0.114 (.76)	3.0 (.86)	0.34; {0.36}

2.1.4.4 Performance trends in 28 technological domains

Magee et al. (2014) note that there is considerable ambiguity in many technological studies concerning unit of analysis, choice of dependent variable or performance metric definition, and data quality. The choice of unit of analysis is obviously dictated by the goal of the study. Some economists, for example Solow 1956, have considered technology as a whole as a unit of analysis. At the other extreme, single specific designs may be also studied as a unit of analysis (Wright 1936). Others, such as Moore (2006), have used a unit of analysis, which considers multiple generations of designs, which can be viewed as technological domains, or industries. Being explicit about what the unit of analysis is necessary to compare results consistently between different studies.

Considerable variation also exists in the appropriate definition of performance metric (choice of dependent variable) for a given technology. Some have considered only a single figure of merit for a technology, such as speed of a fighter jet (Lienhard 2008). Others have combined two figures of merit to create a composite, such as seat-miles-per-year capacity (Martino 1971, Tushman and Anderson 1986). A good performance metric should utilize all essential figures of merit (Magee et al. 2014) to prevent trade-offs from appearing as performance improvement. Another important consideration in metric definition is whether the performance metric is intensive or extensive. Use of intensive performance is necessary to capture whether the improvement is due to change in scale or due to inherently a better solution. In this regard, the inclusion of resource constraints in the metric definition is important. Some common examples of resources are cost, volume or mass of an artifact, and time duration. The performance metrics presented in Magee et al (2014) reflect these considerations. A composite performance metric constructed for milling machine, for example, uses three figures of merit – speed (a proxy for measure of production), tolerance (measure of quality), range of manufacturable part size (measure of flexibility), and one resource constraint - cost.

Magee et al. (2014) use functions and bodies of knowledge as two criteria to identify technology domains, the units of analysis in their work. Following the earlier works of Koh and Magee (2006, 2008), they have utilized the operation–operand matrix to capture a range of functions. Table 2.2 shows the 9-cell matrix, where operands – information, energy, and materials – are on the top row, and operations – storage, transportation, and transformation - are on left-most column. Each of the 9 cells – intersections of operands and operations – represents a function. For example, information storage, and energy storage are different functions. Each function can be achieved using different "effects", that is, different bodies of knowledge, thus qualifying them as technological domains. For example, energy can be stored using batteries, capacitors, or flywheels, but the effects they take advantage of are different. Batteries utilize knowledge of electro-chemistry, whereas capacitors and flywheels use knowledge of electro-statics and mechanics respectively. Accordingly, each of these represents a domain. The table 2.2 lists 28 domains used throughout this thesis along with the body of knowledge they utilize.

In order to clarify for readers the nature of empirical performance data, performance data for two sample domains – electric motor and MRI - are presented (Fig. 2.8a). The data set for each domain contains only non-dominated observations for determining the trends[6]. Non-dominated observations are those observations, whose value has not been achieved earlier in time; in other words, they are record setters. It has to be noted that the plots use a logarithmic scale on the vertical axis (performance) and linear scale on the horizontal axis (time).

There are two patterns to note on this plot. First, the each data set can be approximated by a straight line (R^2 is 0.85 or higher for both), implying that the improvement is described well by an exponential with time. The exponential trend for each domain can be described by equation 2.2, where $Q_J(t)$ and $Q_J(t_0)$ are the intensive performance of an artifact in domain J at time t and t_0, and K_J is the annual rate of improvement of the domain in question. Second, the rate of improvement for MRI, equal to 21.3%, is much higher than that for electric motor, equal to 3.1%.

Magee et al. (2014) extended the study to 73 different performance metrics in 28 different technology domains. All metrics continue to exhibit exponential trends, and the variation is even greater, ranging from 3% for milling machines to 65 % for optical telecommunications. Figure 2.8b provides a summary of improvement rates for 28 domains displayed with decreasing K.

These empirical patterns provide the context for the theoretical work in the current thesis. In a related work, Benson and Magee (2015b) have empirically investigated the variation of the improvement rates in these 28 domains. The work has important relationships to the current work so it is described not only to note the relationships but to also clarify the fundamental differences. Benson and Magee found strong correlations between specific meta-characteristics of the patents in the 28 domains[7] and the improvement rate in the domains (a key concern of this thesis as well). These authors found that patent meta-characteristics reflecting the importance (citations per patent by other patents), recency (age of patents in a domain) and immediacy (the average over time of the usage of current new knowledge in the domain) are all correlated with the

[6] It is the usual preferred practice because of concern that dominated points may be exceedingly high on a missing variable introducing noise (Magee et al. 2014)

[7] The patents are found by a new technique developed by Benson and Magee 2015a.

improvement rate. They found a particularly strong correlation ($r= 0.76$, $p =2.1x\ 10^{-6}$) with a metric that combines immediacy and importance (the average number of citations that patents in the domain receive in their first three years). The findings (and associated multiple regressions) are robust over time and with domain selection and are of practical importance in predicting technological progress in domains where performance data is not available (Benson and Magee, 2015b). Nonetheless, the conceptual basis for the findings is observed attributes of the inventive output from a technological field (importance, recency and immediacy of a patent set) and not the process of invention nor other technical aspects of designed artifacts in the domain. The aim of the work reported in the present thesis is to develop a model that yields insights about the pace of change without recourse to concepts based upon observation of the output over time. If fully successful, we would be able to judge the potential for change based only upon the nature of the design knowledge and we might even be able to find new approaches that might achieve technological goals at more rapid improvement rates.

#	Information	Energy	Material
Storage	**Semiconductor Information storage** *(Solid-state physics, chemistry)*	**Electrochemical batteries** *(Electro-chemistry)*	
	Magnetic information storage *(magnetic materials)*	**Capacitors** *(Electrostatics)*	
	Optical information storage *(Optical materials)*	**Flywheel** *(Mechanics, materials)*	
Transportation	**Electrical telecommunication** *(Electromagnetism)*	**Electrical power transmission** *(electromagnetics)*	**Aircraft transport** *(Aerodynamics, mechanics)*
	Optical telecommunication *(photonics, optics)*	**Superconductivity** *(solid state physics)*	
	Wireless telecommunication *(Electromagnetism))*		
Transformation	**IC Processors** *(Solid-state physics, chemistry)*	**Combustion engines** *(Thermodynamics, mechanics)*	**Milling Machines** *(Mechanics, dynamics)*
	Electronic computation *(Solid-state physics, computation)*	**Electrical motors** *(Electromagnetism)*	**3D printing** *(Materials, computation)*
	Camera Sensitivity *(Photonics)*	**Solar PV power** *(Solid-state physics)*	**Photolithography** *(Chemistry, optics)*
	MRI *(Nuclear physics)*	**Wind turbines** *(Aerodynamics, mechanics)*	
	CT scan *(Atomic physics, computation)*	**Fuel cells** *(Physical Chemistry)*	
	Genome sequencing *(biology, genomics)*	**Incandescent Lighting** *(materials)*	
		LED lighting *(Solid-state physics)*	

Table 2.2: Functional matrix with technological domains. Each technological domain is defined by the function and the scientific knowledge used to fulfill that function. Adapted from Magee et al. 2014.

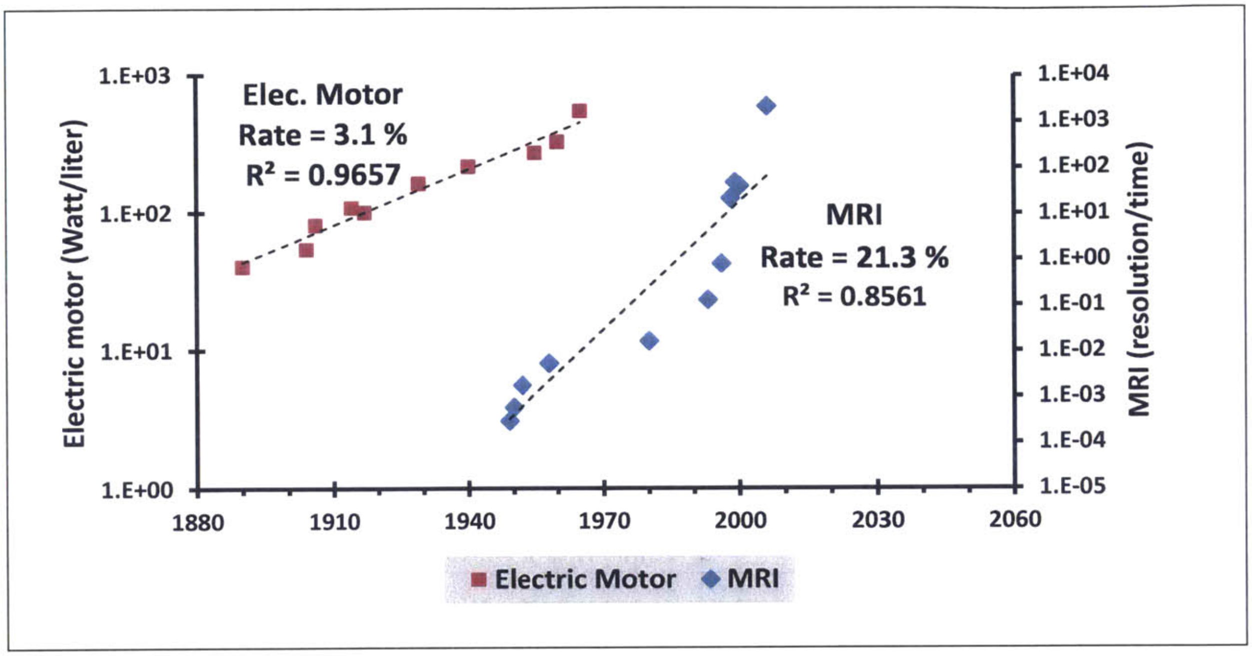


Fig. 2.8a Exponential growth of performance in sample domains. Adapted from Basnet and Magee 2015.

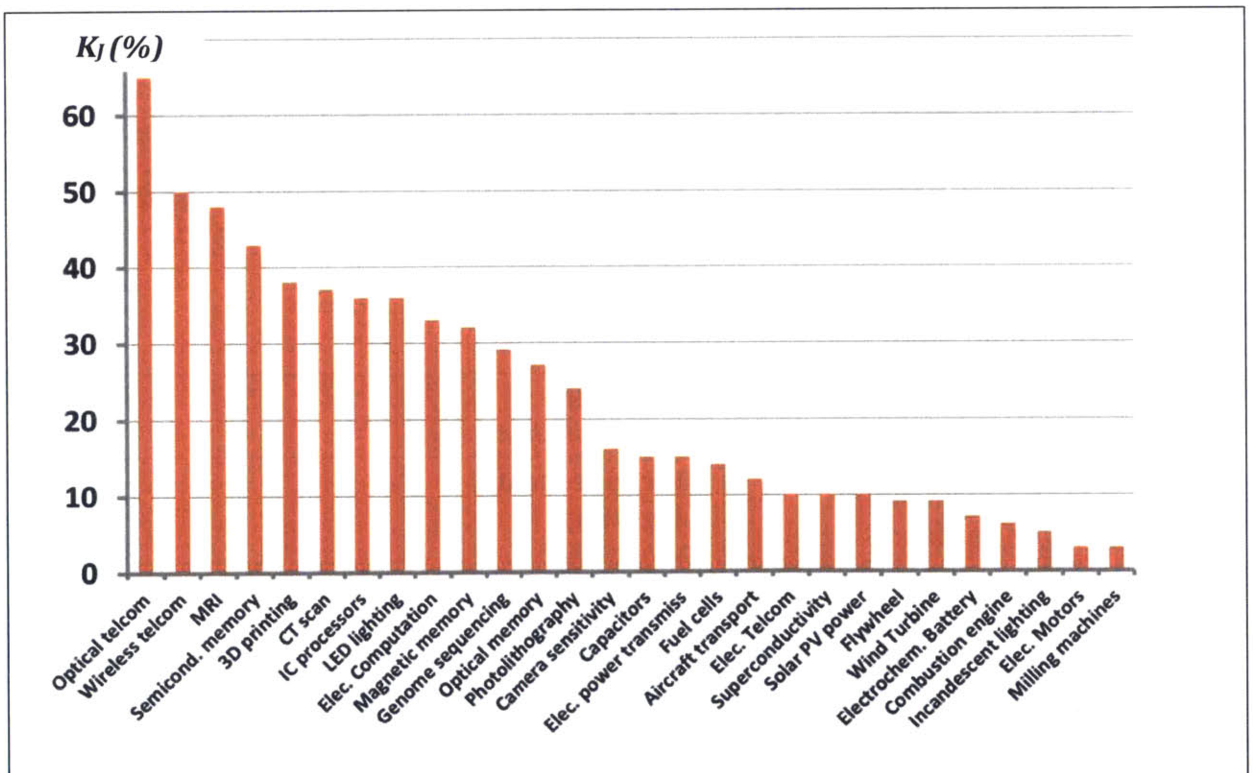


Fig. 2.8b: Annual rate of performance improvement (K_J) for 28 domains. Adapted from Basnet and Magee et al. 2015.

2.2 Design Science Research

2.2.1 Technical Change and Design Science

What connections between technological change and design research (science) can be inferred from the existing literature? Although early literature connecting these two fields is scant, among later works that have begun to build a bridge between aspects of design research and the economics of technological change is the paper by Baldwin and Clark (2006). These authors (and Luo J. et al. 2014) point specifically to a central role for design in achieving economic value. Baldwin and Clark summarize this connection succinctly:

> *"Designs are the instructions based on knowledge that turn resources into things that people use and value. All goods and services have designs, and a new design lies behind every innovation. Clearly then designs are an important source of economic value, consumer welfare and competitive advantage for individuals, companies and countries."*

The authors, at the same time, lament that "despite their pervasive influence, designs as drivers of innovation and wealth creation are not much discussed by social scientists, senior managers, or policy- makers." Very recently, Luo et al. (2014) have analyzed design research in economic context, and assessed four economies –Singapore, Finland, Taiwan, and South Korea – with respect to design capability. Their finding was that the cumulative nature of design, especially technology-based, has important strategic value for sustaining long-term economic growth.

Another view, in addition to one adopted by economists, that somewhat ignores design is the linear model accredited to Vannevar Bush (1945), which considers technical change occurring through application of science (which will be discussed shortly in section 2.2.2). As a counterview, in his seminal book, *The Sciences of the Artificial*, Herbert Simon (1969, 1996) was the first to highlight that design is an activity standing on its own right, like natural sciences, and has its own set of logic, concepts, and principles. While the primary goal of natural science is to produce predictive explanations of natural phenomena, the primary goal of design is to create artifacts, physical or abstract. The design activity is central to creation and improvement of artifacts in all technological domains and involves a cognitive element. This indisputable cognitive element has been noted by many scholars who have studied invention and design (Simon 1969, Dasgupta 1996, Gero and Kannengiesser (2004), Hatchuel and Weil 2009).

The following sub-sections will review related design and invention literature in the context of performance improvement, an important aspect of technical change, and the focus of this thesis.

2.2.2 Design and invention

2.2.2.1 Design theories

In the context of realizing higher performance from subsequent generations of artifacts, the role of invention, as one outcome of the design process, is a critical one since improvement in performance of artifacts must strongly reflect the inventions.[8] As Vincenti (1990, pg. 230) puts it, inventive activity is a source of new operational principles, and normal configurations that underlie future normal or radical designs. The operational principle (Polyani 1962, Vincenti 1990) of an artifact describes how its components fulfill their special function while combining to an overall operation to achieve the function of the artifact.

Models that have been found useful in describing the creative design process include FBS theory (Gero and Kannengiesser 2004), CK theory (Hatchuel and Weil 2009), axiomatic design (Suh 2001), TRIZ (Altshuller 1984), agent-based synthesis (Campbell et al. 2000), topological structures (Braha and Reich 2003), infused design (Shai et al. 2009), analytical product design (Frischknecht et al. 2009) and other models. FBS (Function-behavior-structure) framework models design process as a "recursive interrelationship between different environments" (external, internal to designer, and expected), where each environment can evolve dynamically. CK theory, on the other hand, conceptualizes creation

[8] A design is considered an invention when it is deemed to be historically original (Dasgupta 1996).

of innovative solutions as recursive interaction between propositional knowledge space and design concept space as the design evolves. Axiomatic design is founded on two central axioms – independence of functional requirements and minimization of information content of design. It uses matrix methods to analyze transformation of design parameters into functional requirements. TRIZ contends that, although inventions are products of cognitive insight, there is a pattern that cuts across the industries in the types of problems being solved and the inventive solutions developed. These patterns in problems and solution identified through empirical study of global patents can be used to solve new inventive problems.

Topological structures (Braha and Reich 2003) provide a mathematical framework for studying design processes. The infused design approach (Shai et al. 2009) is aimed at aiding the designers to generate creative conceptual design by transforming solutions from one field to new fields, and uses formal principles. The agent-based approach (Campbell et al. 2000) provides a general methodology for searching unstructured design spaces based on the collaboration of many goal-directed agents, and utilizes "an agent architecture, a multi-objective design selection scheme, a functional representation of solutions, and an iterative-based algorithm for evolving optimally directed design states".

These frameworks briefly noted in this subsection are more concerned with the cognitive details of generating a specific design, and do not consider previous and future generations of artifacts; hence they appear less promising for modeling performance changes.

2.2.2.2 Invention and combinatorial analogical transfer

The modeling framework found most helpful in our modeling of performance changes resulting from a cumulative design process is analogical transfer. Although this idea can be traced as beginning with Polya (1945) or earlier, the framework remains an active area in design research (Clement et al. 1994, Goel 1997, Gentner and Markman 1997, Leclerq and Heylighen 2002, Dahl and Moreau 2002, Christensen and Schunn 2007, Linsey et al. 2008, Tseng et al. 2008, Linsey et al. 2012, Fu et al. 2013). Weisberg (2006) explains analogical transfer as involving the use of conceptual knowledge from a familiar domain (base) and applying it to create knowledge in a domain with similar structure (target): analogical transfer exploits past knowledge in both the base and target domains. The analogies utilized can be local, regional or remote, depending on surface and structural similarities between objects involved in the base and target domains. Weisberg discusses the example of the Wright brothers using several analogical transfers to recognize and solve the problem of flight control. First, the Wright brothers viewed flying as being similar to biking in which the rider has to be actively involved in controlling the bike, an application of regional analogy. Interestingly, many others attempting to design artifacts for flying did not access this regional analogy and thus did not even identify the key control problem. Second, they studied birds to see how they controlled themselves during flight, and learned that they adjusted their position about the rolling axis using their wing tips. From this insight, they had the idea of using similar moving surfaces, another instance of using regional analogy. Lastly, they developed the idea of warping the wings, demonstrated by using a twisted cardboard box, to act like vanes of windmills to make the airplane roll. The use of three analogical transfers in combination to see and solve the flight control problem is a clear case of analogical transfer but there is also evidence (cited earlier in this paragraph) of much wider applicability. Weisberg contends that analogical transfer is utilized in generation of both scientific and technological knowledge. Existing knowledge provides the foundational basis for analogical transfer to occur.

There are more abstract versions of combinatorial analogical transfer that have been proposed in the wider literature. Based on an extensive historical study of mechanical inventions and drawing insights from Gestalt psychology, Usher (1954) proposed a cumulative synthesis approach for creation of inventions. See Fig. 2.9. Usher conceptualizes inventions occurring through four stages: (1) perception of incomplete pattern (2) the setting of the stage (3) the act of insight (4) critical revision and full mastery of the new pattern. The notion of bisociation (Dasgupta 1996, Koestler 1964) develops this concept – cumulative synthesis approach - further and says that a new inventive idea is ideated combining disparate ideas. More recently, Fleming (2001) and Arthur (2006) have respectively used the same combinatorial notions of invention in studying technical change. Other research in the technical change literature also discusses a related concept that is usually called "spillover". Rosenberg (1982) showed that such technological spillover greatly impacted the quantity and quality of technological change in the United States in the 20th century – a result supported by Nelson and Winter (1982) and Ruttan (2001). Indeed, a recent paper by Nemet and Johnson (2012) states that "one of the most fundamental concepts in innovation theory is that important inventions involve the transfer of knowledge from one technical area to another". These descriptions do not always make a clear distinction regarding whether the transfer is occurring at the idea level or at the artifact level. They are silent regarding how and from where designers or inventors get their disparate ideas to combine.

Analogical transfer of ideas as a mechanism and expertise - scientific and technological knowledge - as the foundation of ideas (Weisberg, 2006) provides specificity adequate for the model in this thesis. We next consider the nature of knowledge.

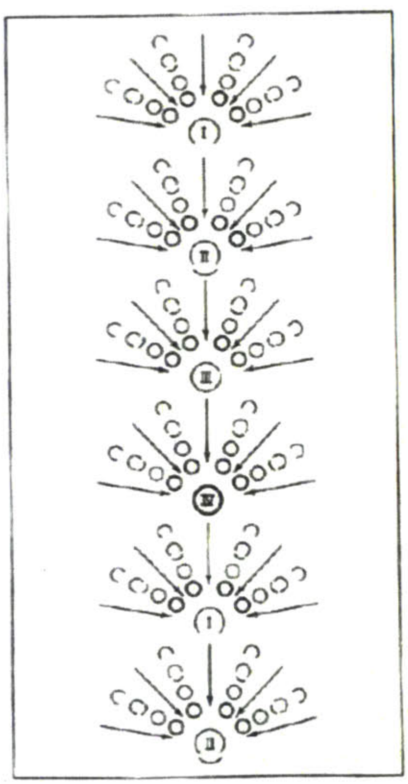


Fig. 2.9: The process of cumulative synthesis. A full cycle of first invention and a part of a second cycle. Large circles I-IV represent four steps in the development of a strategic invention. The steps are: (I) perception of incomplete pattern, (II) the setting of the stage, (III) the act of insight, (IV) critical revision and full mastery of the new pattern. Small circles represent individual elements of novelty. Arrows represent familiar elements in the new synthesis. Adapted from Usher 1956 p 69.

2.2.2.3 Taxonomy of knowledge and operating principles

Vincenti (1990), and Mokyr (2002) take the view that both scientific and technological knowledge can be classified into descriptive (*Understanding*) and prescriptive (*Operations*) knowledge regimes[9]. See Fig. 2.10. The understanding regime can be seen as a body of 'what' knowledge and includes scientific principles and explanations, natural regularities and patterns, materials properties, and physical constants. A unit of Understanding is falsifiable (Popper 1959) and enables explanation and prediction about specific phenomena, including artifacts. However, some principles are fitter than others suggesting explanatory reach as a metric. The operations regime, on the other hand, can be viewed as a body of 'design knowledge', which suggests how to leverage natural 'effects' (Arthur, 2006, Vincenti, 1990) to achieve a technological advantage or purpose. It includes, operating principles, design methods, experimental methods, and tools (Dasgupta 1996, Vincenti 1990). An example may help clarify this distinction: the principle of total internal reflection (Fig. 2.11) says that a beam of light, incident at an angle greater than a certain critical angle, will get fully reflected when it tries to go from a denser medium, such as glass, to a lighter medium, such as air. This principle accurately describes a natural effect, but it does not prescribe how we can use it to transmit information. Total internal reflection of a beam of light between a pair of parallel surfaces (or within a fiber) encompassing a denser medium provides a mechanism – an operating principle - to make a ray of light travel down the length of a medium. Based on this distinction, understanding enables generation of operational knowledge, which ultimately contributes towards design of some artifact. However, operations is not entirely based upon existing understanding and in fact innovations in know-how can and often do occur before any understanding of related natural effects is available. Development of steam engine, for example, spurred the birth of thermodynamics (Hunt 2010).

[9] We use the terms "Understanding" and "Operations", since each brings more clarity to the nature of underlying activity. Understanding refers to conceptual insight that is generated about an object or environment, whereas operations refer to the idea of acting on an object or environment to get some desired effect. Bruce Hunt (2010) describes this as *knowing* versus *doing*.

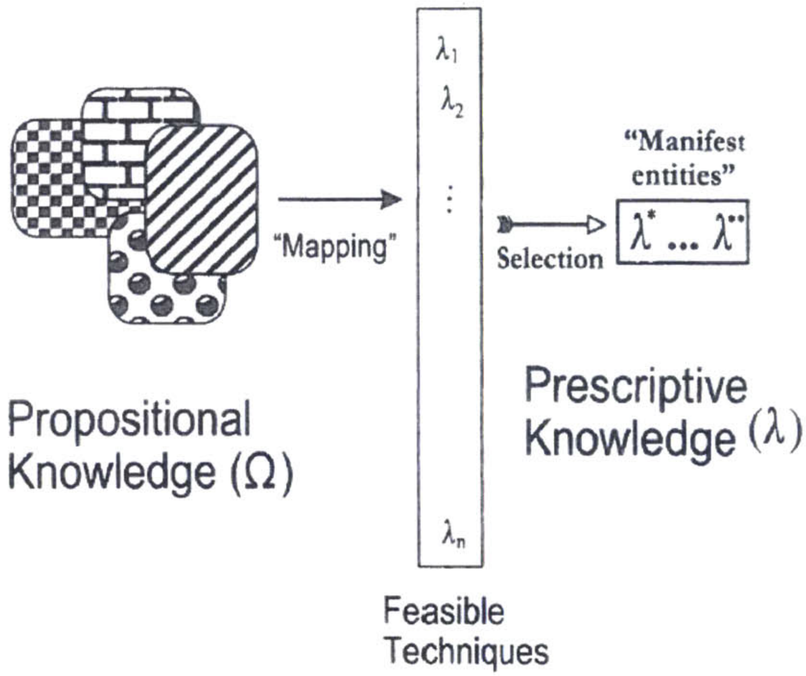
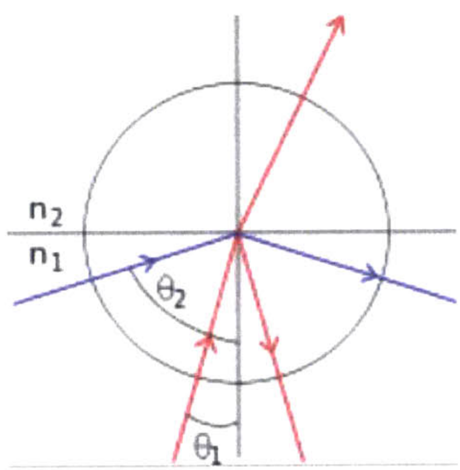
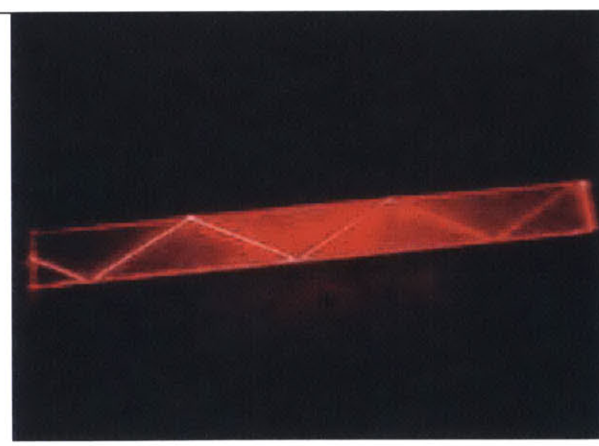


Fig. 2.10: Propositional (*Understanding*) and Prescriptive (O*perations*) knowledge. Adapted from Mokyr, 2002, p 17.



a) Total internal reflection



b) Embodiment of total internal reflection to transmit energy or information using parallel surfaces or a fiber

Fig. 2.11: Example of understanding and operating principle

Weisberg (2006) has emphasized that analogical transfer is used in a variety of creative activities including science (close to our understanding regime) and invention (close to our operation regime except that operations also includes the experimental tools of science). A similar argument has been applied to the more abstract notion of combinations. For example, Ruttan (1959) argued that Usher's formulation, cumulative four step process, "provides a unified theory of the social processes by which 'new things' come into existence that is broad enough to encompass the whole range of activities characterized by the terms science, invention, and innovation". We will utilize models of both the understanding and operation regimes that are based upon analogical transfer of knowledge to (probabilistically) create new knowledge.

2.2.3 Synergistic exchange between science and technology

An important aspect of design and invention is the cooperative link between understanding (science) and operations (technology) regimes (Musson, 1972, Musson and Robinson 1989). Using a historical perspective, Mokyr (2002) has carefully observed that a synergistic exchange between the two has been occurring, where each enables the other (see Fig.2.12). The contribution of understanding (science) to operations (technology) is well known: it provides principles, and regularities of natural effects, including new ones, in the form of predictive equations, and descriptive facts, such as material properties. Fleming and Sorenson (2004) provide evidence that understanding helps inventors by providing a richer map to search for operating ideas, which can be combined together. Understanding also provides insight about where new technological opportunities may be found (Klevoric et al. 1995). Beyond these contributions, there is a more general view (for example Arthur, 2006) that new technology (new operating ideas) can be derived from new scientific knowledge (understanding). What is less discussed is the contribution of operations to the understanding regime.

The linear model of innovation, often identified with Vannever's Bush report (1945), does not include the enabling role played by technology in scientific research. The Linear model as presented by Balconi (2010) and others (Godin 2006), consists of four stages: basic research, applied research, development, and production, in which knowledge flows one way only. The advocates of linear models, especially early natural scientists, argued that primary seeds of innovative products originated in science. Vannevar Bush (1945), as quoted by Balconi (2010), epitomizes this sentiment:

> *"We will not get ahead ... unless we offer new and more attractive and cheaper products. Where will these new products come from? How will we find ways to make better products at lower cost? The answer is clear. There must be a stream of new scientific knowledge to turn the wheels of private and public enterprise." (Bush, 1945, http://www.nsf.gov/ about/history/vbush1945.htm#ch3.5)*

Several works have aided in correcting this oversimplified linear view; they emphasize the contribution made by technology to scientific research. In his paper, *Sealing wax and string*, de Solla Price (1986), a physicist, and historian of science, highlighted that instruments (an output of the operations regime) were a dominant force in enabling scientific revolutions. He states: "... changes in paradigm that accompany great and revolutionary changes (in science) were caused more often by application of technology to science, rather than changes from 'putting on a new thinking cap' ". Historian of science Peter Galison (1987), as cited by Baldwin and Clark (2006), reminds us that "scientists will go where their tools of observation and analysis take them, but can go no further." Operations provides tools and instruments to make measurements, and to make new discoveries. In his book, *The Scientist: A History of Science Told Through the Lives of its Greatest Inventors*, Gribbin (2002), a British astrophysicist, and science writer, has described how the ability to grind eyeglass lenses made it possible to make better telescopes, and hence paved the way for astronomers to make new discoveries. Operations aids also by providing news problems to solve for understanding (Laudan 1984, Vincenti 1990, Hunt 2010). Overall, new or improved observational techniques are still a major driver of progress in science.

Gribbin (2002) has aptly summarized the enabling exchange between the two regimes: "new scientific ideas leading... to improved technology and new technology providing scientists with the means to test new ideas to greater and greater accuracy". Based upon these insights and with our focus on explaining technological changes from continuing streams of invention, our model treats mutual exchange between understanding and operations.

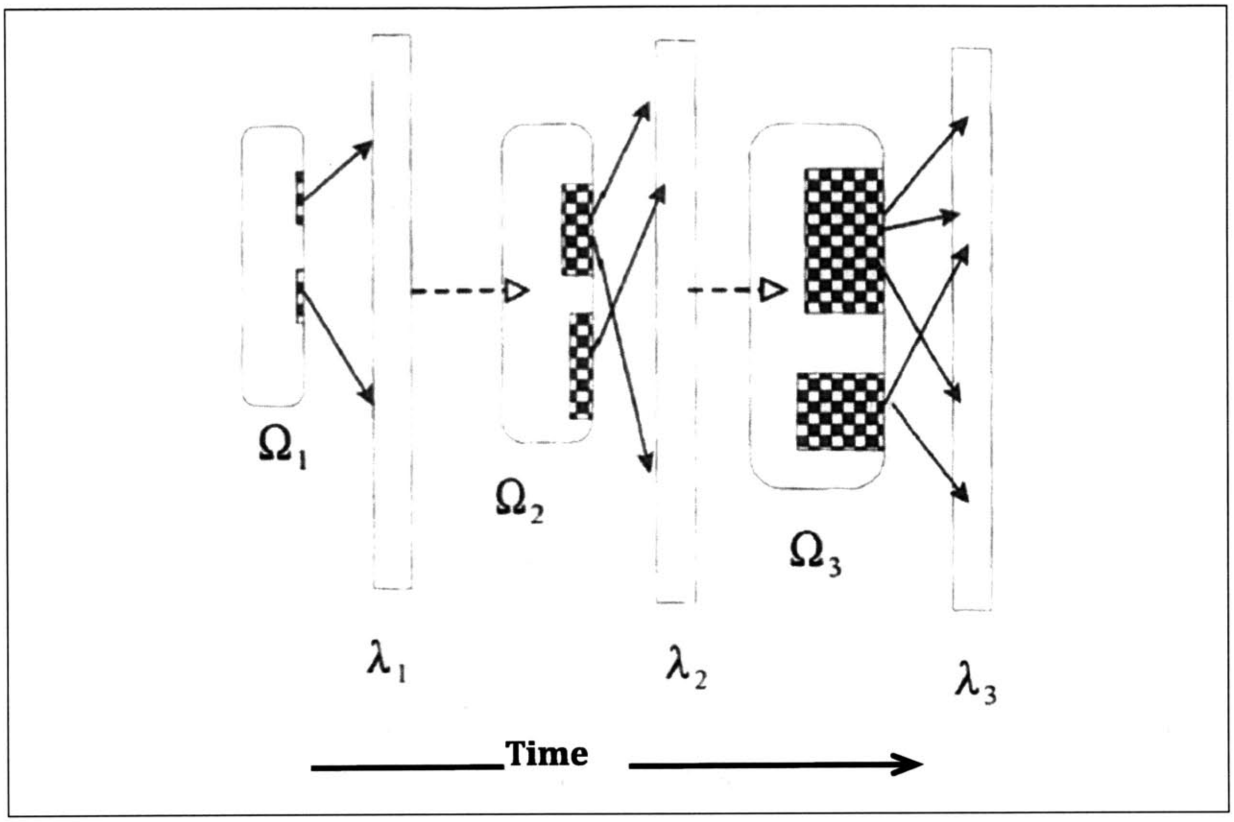


Fig.2.12: Feedback between understanding (Ω) and operations (λ). Useful understanding (Ω) - checkered area - informs creations of operations (λ), which in turn aids in expanding understanding (Ω), and the cycle continues over time. Adapted from Mokyr 2002, p 22.

2.2.4 Interactions in domains artifacts

Two important facets of domain artifacts – interactions and scaling - provide important insight in modeling of performance variation across domains. In design of artifacts, Simon (1962) introduced the notion of interactions in his essays on the complexity of artifacts. When a design of an artifact is changed from one state to another (with differences between the two states as defined by multiple attributes, say D1, D2, and D3) by taking some actions (say, A1, A2, and A3), in many cases, any specific action taken may affect more than one attribute, thus potentially leading to interactions of the attributes. The same notion of interaction/conflicts is captured by the concept of coupling of functional requirements (Suh 2001), or dependencies between characteristics (Weber 2003), which can occur when two or more functional requirements are influenced by a design parameter. Theoretically, it seems ideal to have one design parameter controlling one functional requirement to achieve a fully decomposable (modular) design (Suh 2001, Baldwin and Clark 2000). Using an in-depth qualitative analysis of VLSI and complex electro-mechanical-optical (CEMO) systems, Whitney (1996, 2004), however, has strongly argued that, in reality, how decomposable a design of an artifact can be depends on the physics involved or additional design constraints, such as permissible mass. These couplings or constraints manifest as component-to-component[10], and component-to-system interactions, or as a need to have multi-functional components. Consequently, Whitney argues, CEMO systems, primarily designed to carry power, cannot be made as decomposable as VLSI systems primarily designed to transmit and transform information. For example, in energy applications, the impedance of transmitting and receiving elements has to be matched for maximum power transfer, thus making the two elements coupled. Further, CEMO systems typically need to have multi-functional components in order to keep the artifact size reasonable, creating coupling of attributes at the component level. Another highly influential interaction Whitney has identified are the adverse concomitant side effects in artifacts, such as waste heat in computers, or corrosion of electrodes in batteries. These side effects force engineers, working in CEMO systems, to 'often spend more time anticipating and mitigating a wide array of side effects' than 'assembling and satisfying the system's main functions'.

The presence, and thus the resolution, of these different interactions causes significant delay, diverts significant engineering resources and potentially stops applications of some concepts, thus making the level of interactions of a technological domain a potentially strong factor influencing its rate of improvement. Based upon Whitney's work, the effect of interactions on rates of improvement was suggested qualitatively by Koh and Magee (2008) and a quantitative model of the effect was developed by McNerney et al. (2011) - see section 2.3.

[10] Design structure matrices (DSM) (Eppinger and Browning 2012) have been used to study and analyze such interactions in many artifacts (e.g., a commercial airplane jet engine by Pratt & Whitney, an automotive climate control system by Ford Motor Co., Mars Pathfinder by NASA, web browser software by Mozilla open source). DSM for products can capture exchange of information, energy, and materials between components and sub-systems.

2.2.5 Economy of scale and scaling of design variables in domain artifacts

In addition to domain interactions, scaling of design variables in domain artifacts is another potential contributing factor to variation in domain performance. Economists have studied this aspect within the framework of economies of scale. Many economists study economies of scale assuming a constant technology. In chapter 12 *Scale Economies in Economic Growth*, Lipsey et al. (2006), however, reminds us that 'in economic history falling unit costs of output are often observed to accompany many technological changes'. These improvements in economies are due to "historical increasing returns" to scaling made possible by '*permanently embedded ... geometry and physical laws in the world we live in*'. Listing several sources of scaling, they point out that these two sources are the most important in technological change. However, our ability to exploit these scaling effects in these geometrical and physical scaling is '...limited by the current state of technology'. 'New technology is, therefore, required to allow further exploitation of these effects', suggesting inventive ideas as a source for realizing these scaling effects.

In design science and engineering literature, the influence of both geometry and physical laws (which include influence of other physical parameters, such as temperature, and pressure) on performance of artifacts is common knowledge. These geometric and physical parameters are collectively referred to as the design parameters and are primary levers for improving performance. Many technological domains have complex mathematical equations relating some aspects of performance with design parameters. Indeed, the engineering science literature has such equations for many aspects affecting the design of artifacts, perhaps in all technological domains. Simpler relationships concerning the geometrical scale of artifacts are also available and generally give performance metrics as a function of a design variable raised to a power, in other words, expressed as a power law. Use of such power-law relationships can be found in many studies: 1) Following Stahl's (1962) analysis of biological systems[11], Sahal (1985) showed

[11] In biology, scaling effects have been studied as allometric scaling, in which power-laws between physiological metrics (such as heart rate and metabolic rate) and mass of the organisms are sought. In his

through a study of three different sets of artifacts - airplanes, tractors, and computers - that scaling (changing geometrical size) has been instrumental in both spurring and restricting innovation. 2) In his study of blast furnaces, Bela Gold (1974) demonstrated that doubling the size of a blast furnace reduces their cost by about 40%. This constancy of percent change per each doubling in size results from the power law (assumed by Gold) between performance/cost and geometrical variables such as volume.

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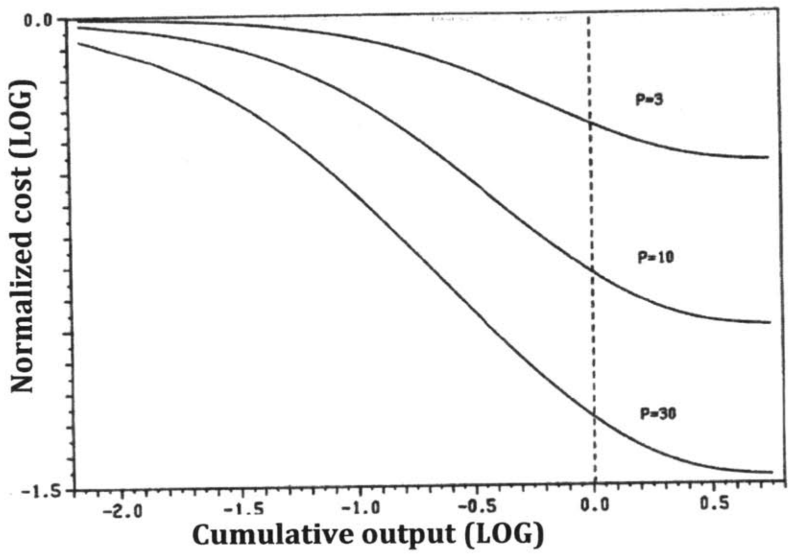
famous book *On Growth and Form*, D'Arcy Wentworth Thompson (1942) has described how mechanics and scaling influences the evolution of structure and form of animals. Similarly, in a famous paper, *Body size and metabolic rate* in Physiological Reviews, Max Klieber presented his observation that metabolic rate of the majority of animals scales as a ¾ power of the animal's mass. McMohan (1973) and Barenblatt (2003) have studied scaling phenomena in physical systems.

2.3 Literature on modeling technological change

What research has attempted to model the technological performance trends that were discussed in section 2.1.4? Much of the related research effort has been focused on modeling Wright's results, with recent works adding the concept of interactions into the models. Agent-based and combinatorial simulation models deviate from this modeling tradition.

Muth (1986) developed a model to explain Wright's results by introducing the notion of search for technological possibilities. In his paper, he reviewed number of prior models developed by March and Simon (1958), Crossman (1959), Levy (1965), Sahal (1979), Robert (1983) and Venezia (1985) to explain Wright's results. He contends that these 'theories in the literature either fail to agree with the main empirical phenomena or else assume precisely what they attempt to explain.' For example, an early model developed by March and Simon resembles search theory and relies on "performance gaps", the difference between actual and desired performance. This implies that the greater the performance gap, the higher the improvement activity. According to Muth, this further implies that organizations in trouble are the most innovative. This is simply not the case (Mansfield 1961). Levy (1965) and Sahal's (1979) models assume the change in production rate (inverse of unit cost) is proportional to the amount that the production process can improve. Although they lead to initial concavity and eventual plateauing, no distinct power-law behavior – linear behavior in log-log scale - is exhibited in the intervening period, the most important aspect of Wright's relationship (see Fig. 2.13). Most importantly, their proportionality relationships are not based on any organizational behavior or inventive mechanism.



Note the absence of clear linear regions in the curves.

Fig. 2.13 Relative cost as a function of cumulative output, according to the Levy (1965) model. P is the plateau output rate. Adapted from Muth 1986.

The model by Muth (1986) noted above is an alternative way to explain Wright's results introducing the notion of search for technological possibilities. He assumes that random search for a better technique, a key element of technological problem solving, is made within a fixed population of possibilities. Considering a case of a single manufacturing process, Muth (1986) developed his model based on statistics of extremes to capture the idea of substituting manufacturing sequences with better ones. He argues that shop personnel improve the process by learning through experience and making random search for new techniques, which enable improvement of processes leading to cost reductions. Muth demonstrated that the notion of fixed possibilities easily leads to fewer and fewer improvements that can be realized, which results in unit cost reducing as a power law with respect to production (see Fig. 2.14). He argues that his model with fixed technical possibilities can accommodate a leveling off and eventual stoppage in cost reduction. Muth, however, does not reference Sahal (1979) and seems unaware of the coupling of power laws and exponentials.

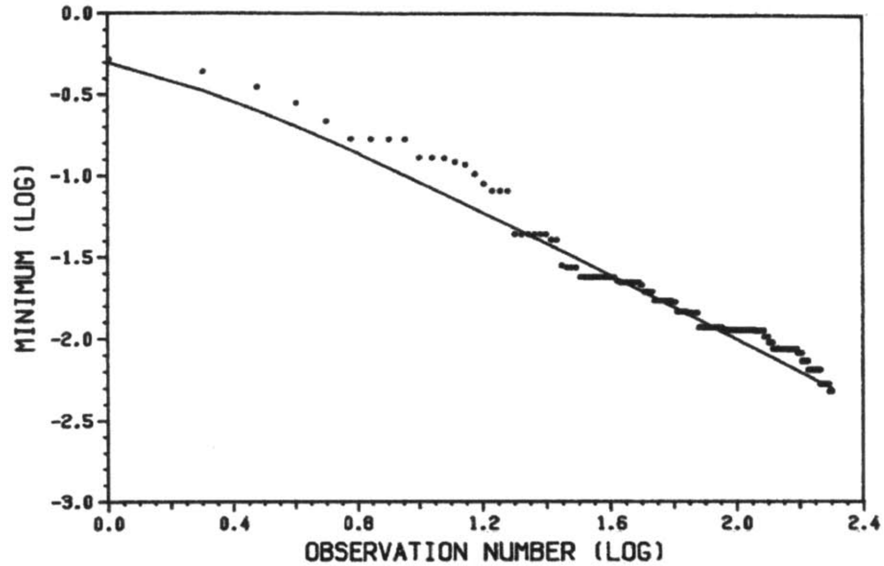


Fig. 2.14 Simulated process costs drawn from uniform distributions. Number of operations in process = 10. Adapted from Muth 1986.

Building on Muth's idea of random search within a set of fixed design possibilities, Auerswald et al. (2000) developed a microeconomic model of a complex multi-process manufacturing system, in which different processes can be combined to create diverse production recipes. They introduced for the first time the notion of interactions by allowing adjoining processes to affect each other's cost. It is important to note that since the predominant experimental regime in the Wright framework is for a singular design, it is appropriate that Muth and Auerswald do not consider cognitive aspects of design.

Following similar reasoning as Muth and Auerswald, McNerney et al. (2011) have developed a stochastic model to explain how the rate of cost reduction (reciprocal of performance improvement) of a multi-component system is influenced by component interactions, which they refer to as connectivity between components. McNerney et al. have operationalized the notion of interactions as out-links representing influence of a component on other components, which they capture using design structure matrices (DSM). When a specific component in a domain artifact is changed by introducing a new operating idea[12], it affects the design of all the components it influences. If the performance of the artifact (influencing and influenced components) as a whole improves, then the interactions are said to be resolved and the operating idea is said to be successful. They have shown that cost reduction (or performance improvement) proceeds at a faster rate in multi-operation production recipe that have fewer interactions than in those that have higher number of interactions (see Fig. 2.15). This finding can be extended to the idea that if the domain artifacts have fewer interactions, then designers have a higher chance of resolving interactions for each operating idea they introduce.

Using agent-based modeling, Axtell et al. (2013) have developed a competitive micro-economic model of technological innovation utilizing the notion of technological fitness. Although they do not discuss or cite Moore's law or his work, they have demonstrated that all agents, utilizing combinatorial process, increase their cumulative technological fitness exponentially overtime. This is different from other researchers who have predominantly been focused on Wright's framework. Consistently, Axtell et al. consider new designs and not just process optimization.

Using a simulation approach, Arthur and Polak (2006) have modeled how new generations of artifacts arise by combining currently available artifacts. The artifacts considered are electronic logic gates and new generations are represented by more developed logic gates that can then also be combined to give even more complex logic gates. In their model, Arthur and Polak specify several design goals towards to which the logic gates evolve. They have demonstrated that designs with higher levels of complexity cannot be attained without realizing design configurations with intermediate levels of complexity, and new designs with higher functionality substitute for current designs with inferior functionality. This model is much richer than other models in representing the artifact part of the design process; however, it does not consider performance improvement, as do the other models. It is also limited to developing pre-specified artifacts and is thus a specific process but is not open-ended or general, which are characteristics necessary for modeling performance trends for general technological domains.

[12] Although McNerney et al. do not distinguish between operational and understanding nor between ideas and artifacts, the text accurately represents their model.

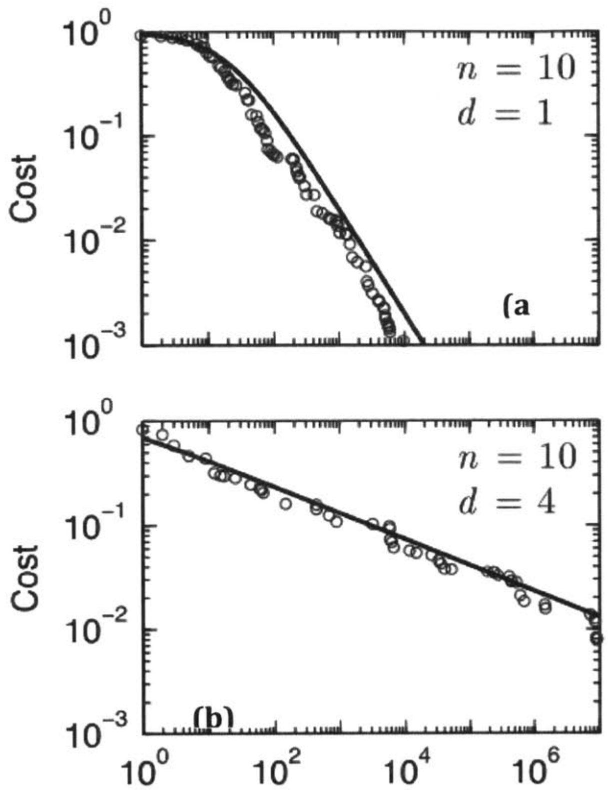


Fig. 2.15 Simulation (circles) and predicted (solid curves) results comparing cost reduction rates (slopes) between two recipe models that have different interactions (out-links, d). In each case out-links d is constant for each process: (a) out-links, d=1; (b) out-links d=4.
Adapted from McNerney et al. 2011 pp. 9010.

Although some are more explicit than others, one feature common to all these models is that all utilize the notion of building upon the performance (in the form of cost) or designs of the past, a key feature of cumulative processes. On the other hand, they do not consider two aspects we believe useful in answering our research question. First, none consider the design process as part of their model and thus do not consider analogical transfer or operating ideas. All consider search or combination at the artifact level - components instead of ideas. Second, none of them discusses or includes the influential role played by exchange between science and technology. In this thesis, we treat the design process and the exchange between science and technology as important elements for understanding the change in performance over time that in turn is essential to understanding technological change.

2.4 Literature review of patents and content analysis

The mathematical model developed in this research suggests that an interaction parameter associated with a domain plays an important role in influencing its rate of improvement. This prediction has been tested in this research using textual content from patents. This section provides a broad overview of the patent literature. Items of importance for this thesis are emphasized, specifically the structure and content of patents, and identification of relevant patents in technological domains.

2.4.1 Overview of U.S. patents

United States Patent and Trademark Office (USPTO) grants three types of patents – utility, design, and plant. The majority of inventions issued by USPTO are of the first type and are the subject of this research. Utility patents include processes, machines, manufactured articles, and material compositions, including improvements to each of these categories. To be eligible as a utility patent, a claimed invention needs to qualify as novel, non-obvious, and useful. An invention is *not* considered novel, if:

> "(1) the claimed invention was patented, described in a printed publication, or in public use, on sale, or otherwise available to the public before the effective filing date of the claimed invention" or
>
> "(2) the claimed invention was described in a patent issued [by the U.S.] or in an application for patent published or deemed published [by the U.S.], in which the patent or application, as the case may be, names another inventor and was effectively filed before the effective filing date of the claimed invention." (USPTO 2015)[13].

In other words, the invention has to be historically original. Additionally, the invention being 'patented must be sufficiently different from what has been used or described before so that it may be said to be non-obvious to a person having ordinary skill in the area of

[13] http://www.uspto.gov/patents-getting-started/general-information-concerning-patents#heading-5

technology related to the invention' (USPTO 2015). For example, miniaturization of a prior art would not be ordinarily patentable. Finally, the invention has to be useful by providing practical benefit to the society. This is usually assessed by the invention's operative-ness; in some cases, however, it might be based on theoretical foundations[14].

2.4.2 Structure and content of patents

A patent document can be broadly viewed as consisting of bibliographic data including patent attributes, and content - textual and graphical data, including descriptions of the invention. The bibliographic data is presented in the first page of the patent, and the textual and graphical in the subsequent pages.

2.4.2.1 Patent bibliographic data (also referred to as metadata)

The bibliographic data has number of fields, denoted by reference numbers in square brackets. A patent issued to a thin-film battery invention is presented as a sample in Fig. 2.16 to illustrate fields and sections; the ones which are of interest have been highlighted.

The patent number, indicated by field [11] shown in the top right corner of the page, is a unique identification number assigned to a granted patent. The patent numbers grow sequentially as new patents are issued, but there is no intelligence associated to them. The patent issue date, field [45], is important because it is used for calculating how long the patent owner, the assignee, can exercise property rights, after which the invention is available for public use. The title, field [54], is self-explanatory and indicates the subject of invention, which in this example is electro-chemical batteries. The patent is granted to inventors, field [75], and the individuals who contributed to the conception of the invention. Since a patent is an example of intellectual property, rights to the invention is assigned to an assignee(s), field [73], who can be the inventors themselves. Typically, the rights to the patents are owned by one or more corporations; in this example, by Martin Marietta Energy Systems. The assignees can change over time as the patent can be sold as property to new owners.

[14] http://www.nolo.com/legal-encyclopedia/qualifying-patent-faq-29120-6.html

US005597660A

United States Patent [19]

Bates et al.

[11] **Patent Number: 5,597,660**

[45] **Date of Patent: Jan. 28, 1997**

[54] **ELECTROLYTE FOR AN ELECTROCHEMICAL CELL**

[75] Inventors: **John B. Bates**, Oak Ridge; **Nancy J. Dudney**, Knoxville, both of Tenn.

[73] Assignee: **Martin Marietta Energy Systems, Inc.**, Oak Ridge, Tenn.

[21] Appl. No.: **248,929**

[22] Filed: **May 25, 1994**

Related U.S. Application Data

[62] Division of Ser. No. 921,538, Jul. 29, 1992, Pat. No. 5,338,625.

[51] **Int. Cl.**^{6} **H01M 10/36**

[52] **U.S. Cl.** **429/191**

[58] **Field of Search** 423/302; 429/191; H01M 6/18

[56] **References Cited**

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4,419,421 12/1983 Wichelhaus et al. 429/191

5,188,768 2/1993 Sotomura .... 429/191 X

FOREIGN PATENT DOCUMENTS

WO9113472 9/1991 WIPO H01M 6/18

Primary Examiner—John S. Maples

Attorney, Agent, or Firm—G. L. Craig; H. W. Adams

[57] **ABSTRACT**

Described is a thin-film battery, especially a thin-film microbattery, and a method for making same having application as a backup or primary integrated power source for electronic devices. The battery includes a novel electrolyte amorphous lithium phosphorus oxynitride which is electrochemically stable and does not react with the lithium anode and a novel vanadium oxide cathode Configured as a microbattery, the battery can be fabricated directly onto a semiconductor chip, onto the semiconductor die or onto any portion of the chip carrier. The battery can be fabricated to any specified size or shape to meet the requirements of a particular application. The battery is fabricated of solid state materials and is capable of operation between −15° C. and 150° C.

2 Claims, 5 Drawing Sheets

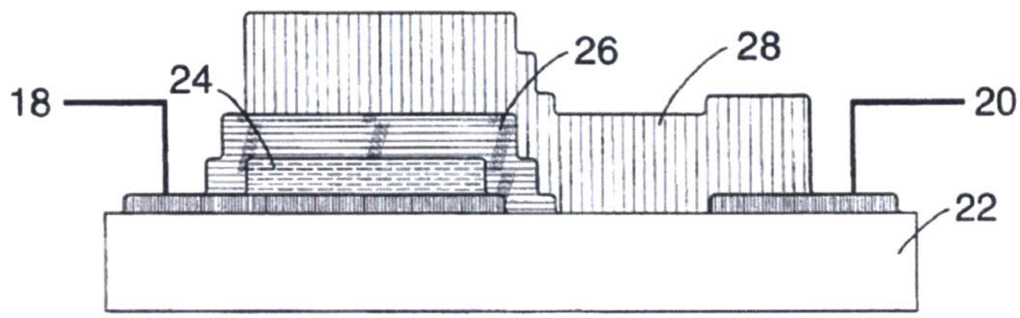

Fig. 2.16: Sample patent, first page

Other than the inventors and assignees, the bibliographic data that has been frequently used in prior technological research is classification codes and citations to prior patents or non-patent literature. US patent examiners assign US patent classification codes, field [52] and International classification codes, fields [51], both of which are used to classify the invention into different technological areas. The difference between these two classification codes will be discussed shortly while reviewing the Classification Overlap Method (Benson and Magee 2013 and 2015a).

Citation to prior literature, including patents, and non-patent literature (such as scientific publications and trade magazines), is included under field [56]. The example patent refers to two US patents and one foreign patent; however, this particular patent does not refer to any non-patent literature. The references are added by the inventors as well as by the examiners in order to show the relatedness of the current invention to prior art. The prior patents that have been referenced are known as backward citations; in contrast, the patents which cite the patent in question are referred to as forward citations (see Fig. 2.17). Both of these data have been used extensively for technological change research to study such phenomena as spillover (Nemet & Johnson 2012).

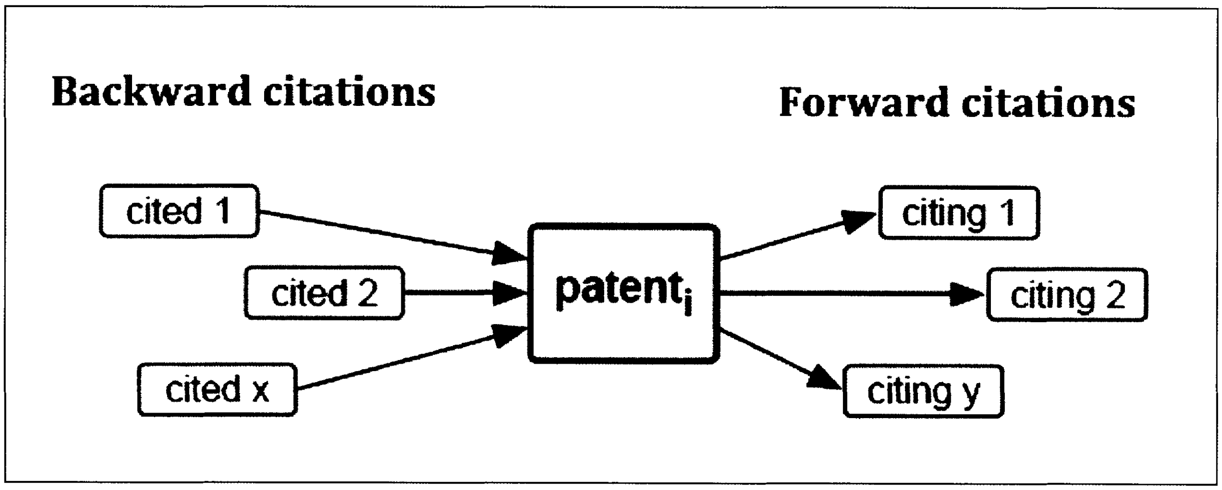

Fig. 2.17: Schema for patent citations showing forward and backward citations to and from patent of interest, i. Arrows indicate flows of knowledge. (Adapted from Nemet & Johnson 2012)

Fig. 1. Schema for patent citations showing forward and backward citations to and from patent of interest, i. Arrows indicate flows of knowledge.

The abstract, the final piece of bibliographic data, provides a short disclosure of the invention and highlights the novelty in the invention.

2.4.2.2 Patent contents- text and drawings

The patent content following the bibliographic data has a number of sections: background, summary, detailed drawings, detailed description, and claims.

The background section, also often referred to as prior art, describes the current state of the technology, and establishes a need for the invention. See Fig. 2.18. The need is typically described in terms of the challenges and problems experienced by the current art. The example patent describes the toxicity and low energy density, and specific energies as some of the limitations of current batteries.

The summary section briefly describes the nature and substance of the invention and highlights salient novel features of the invention. While doing so, however, the summary section often describes problems and challenges the invention is solving, an important feature that is utilized in the empirical study of this research.

The engineering design of a patented invention is described minutely in the detailed description section, covering each aspect of novelty. This section sets the stage for the claims section as well as for sharing the knowledge with the public. The claims section, the final one, discloses all the elements of the invention judged to be novel, which is considered the intellectual property of the inventors/assignee.

2. Description of Prior Art

A battery is one of two kinds of electrochemical devices that convert the energy released in a chemical reaction directly into electrical energy. In a battery, the reactants are stored close together within the battery itself, whereas in a fuel cell the reactants are stored externally. The attractiveness of batteries as an efficient source of power is that the conversion of chemical energy to electrical energy is potentially 100% efficient although the loss due to internal resistance is a major limiting factor. This potential efficiency is

Fig. 2.18: Example description of prior art in patent text.

2.4.3 Selection of patents belonging to technological domains

Two broad classes of techniques exist for identifying patents related to a specific technology: those based on using keywords and those based on using classification codes (USPC or IPC). Since the unit of analysis of the current research is a technological domain, it is necessary to identify patents related to a specific technological domain. The utilized techniques need to provide a relevant and complete set of patents belonging to each technological domain being studied. This section provides an overview of different techniques, with focus on the classification overlap method (COM) used in this thesis to obtain the patents studied.

2.4.3.1 Search techniques based on *keywords*

Keyword techniques use one or more words representing a technology to retrieve related patents. The keywords are used individually or in different combination using Boolean operators, such as 'OR', 'AND' and 'NOT', to make a query encompassing or more specific (Larkey 1999). Although the technique is simple, the choice of relevant keywords for a query often requires expert knowledge of the technical field being considered (Park et al 2013). Since inventors use different words to describe their inventions, keywords representing all aspects of a technology would have to be exhaustive, in order to retrieve complete set of patents. This is not an easy task to accomplish (Baillie 2002) and retrieves many patents that are not relevant as well as those that are.

2.4.3.2 Search techniques based on patent *classification codes*

The patent query techniques based on patent classification codes do not require similar level of domain expert knowledge to find the patents, since they utilize the expertise of the patent examiners in classifying an invention into different technologies (Benson and Magee 2013). A patent is assigned both US patent classification (UPC) and international patent classification (IPC) codes. The UPC codes assigned to a patent are based on the technological fields related to claims made by that invention (Gruber et al. 2013), and it is 'a hybrid of "functional" classes (focused on an aspect an invention) and "application" classes (focused on an industry) US.[15] Each example classification code has a form such as 430/270.1. The three-digit number 430 before the slash represents a class, which in this example is the radiation imagery chemistry, which can include processes, compositions, or products. The number after the slash 270.1 (which can be up to six digits, including three digits after the decimal point) represents a subclass, which in this example is an optical recording nonstructural layered product having a radiation sensitive composition layer.

International classification codes (IPC) are an international patent classification system, which uses a hierarchical structure for classifying patents[16]. Unlike the UPC codes which are based on the technological fields related to the claims, the IPC considers the overall technological nature of the invention to assign the classification codes (Gruber et al. 2013). Each classification term consists of a symbol such as HO1F 1/04 (which represents permanent magnet material). The first letter ('H' = electricity in this example) represents a *section*, followed by two digit numeral denoting a *class* ('01' = basic electric elements). The title associated with a class number indicates basic technological content of the patent. The letter following the two digit number represents a *sub-class* ('F' = magnetic materials based devices e.g., transformers etc.). Finally, the numeral immediately before the slash denotes a *group number* ('1' = technology based magnetic property of materials) followed by *subgroup number* after the slash. ('04' = magnetic alloys).

The patent searches using either the UPC or IPC codes retrieves a large of number of patents. However, results from such searches misses many patents unless numerous codes are used and then often include patents that are not relevant to a specific technological domain. The classification overlap method (COM) developed by Benson and Magee (2013, 2015a), which uses both UPC and IPC together for retrieval, overcomes this shortcoming, and provides relatively complete sets of patents that are largely relevant. For this reason, this technique has been used in this research and therefore is reviewed in greater detail.

[15] http://www.intellogist.com/wiki/US_Patent_Classification_System
[16] http://www.wipo.int/export/sites/www/classifications/ipc/en/guide/guide_ipc.pdf

2.4.3.3 Classification overlap method (COM)

The COM technique for patent search is based on the notion that dual membership of patents in IPC and UPC classes leads to better relevancy results. The technique involves six steps for retrieval of a complete and relevant set of patents for a technological domain (see Fig. 2.19). Step 1 involves retrieving a set of patents, called a seed set, using keywords related to a technological domain. The search is carried out by querying titles and abstracts of patents in a patent database such as PatSnap (PatSnap 2013). In those cases, where the use of keywords does not provide a promising set of relevant patents, use of inventors or assignee's names can be used and might generate a better set of patents.

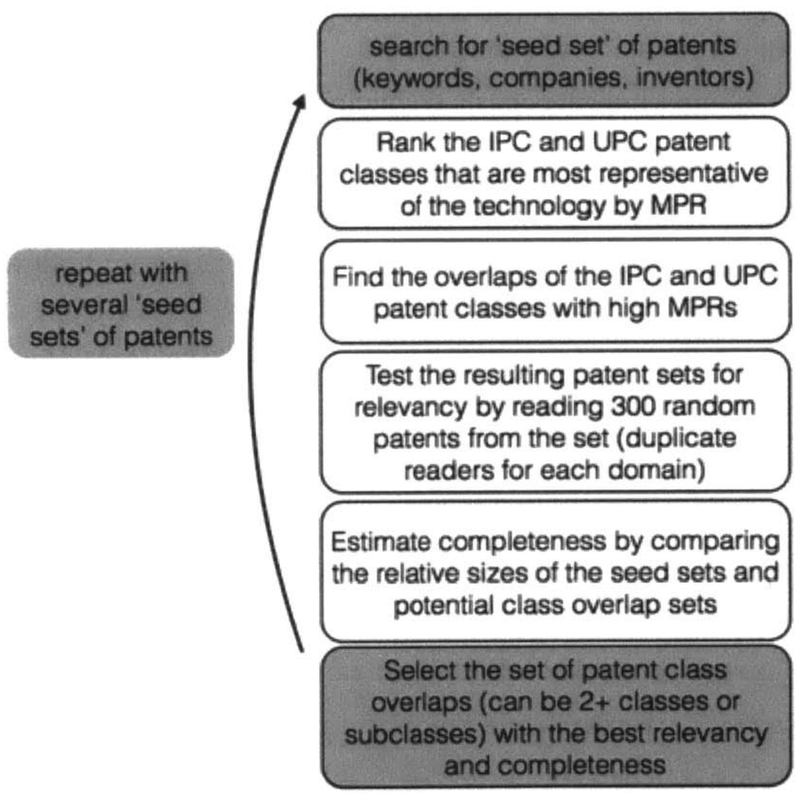

Fig. 2.19: Process flow of COM technique. Adapted from Benson 2013.

In step 2, the UPC and IPC codes that are most representative of a specific technological domain are determined using the list of patents generated in step 1. This step is started by binning all patents from step 1 into different UPC and IPC classes. MPR (mean precision and recall) values are then calculated for each UPC and IPC class. The precision value for a class (UPC or IPC) is defined as a ratio of the number of patents from the step 1 that belong to a particular class to the total number of patents in that class. This calculation requires determining the count of number of patents that belong to a particular class. The recall value is calculated as a ratio between the numbers of patents in the seed set (from step 1) that belong to a particular class to the number of patents in the seed set. The MPR for each class is calculated as an average of their precision and recall values. Ranking UPC classes and IPC classes in descending order based on their MPR values completes step 2.

In step 3, new patents sets are retrieved using overlap (intersection) of UPC and IPC classes with high MPR values. For example, overlap of UPC1 and IPC1 in Fig. 2.20 (Areas A and B considered together) is an example of such an overlap. The set of patents obtained from each overlap of UPC and IPC is inspected by reading of titles and abstracts to assess how relevant the patents are, and whether extraneous patents are also included. This inspection will give insight as to whether it is judicious to include more than one UPC or IPC classes to get a complete set of patents for a domain. Another helpful metric in the search is the number of patents obtained. Too high a number might indicate inclusion of many irrelevant patents. This can, for example, happen when applications of a technology are also included. This might signal that use of subclasses might make the search more specific. On the other hand, if the number of patents is small, it might indicate more classes might need to be included to make the set more complete. The best sets of patents are tested for relevancy.

The relevancy study (step 4) is conducted by taking 300 patents chosen randomly from each selected sets. The two or more readers need to independently read the title and abstracts of each of the 300 patents to determine if the patents belong to the domain in question. The two readers are required to increase the objectivity of results, since reading and judging by a single reader might involve excessive subjectivity. If the relevancy of the

300 patents is low, say 50%, it is not an acceptable group of patents. If, however, the relevancy is high, say 85%, it is acceptable.

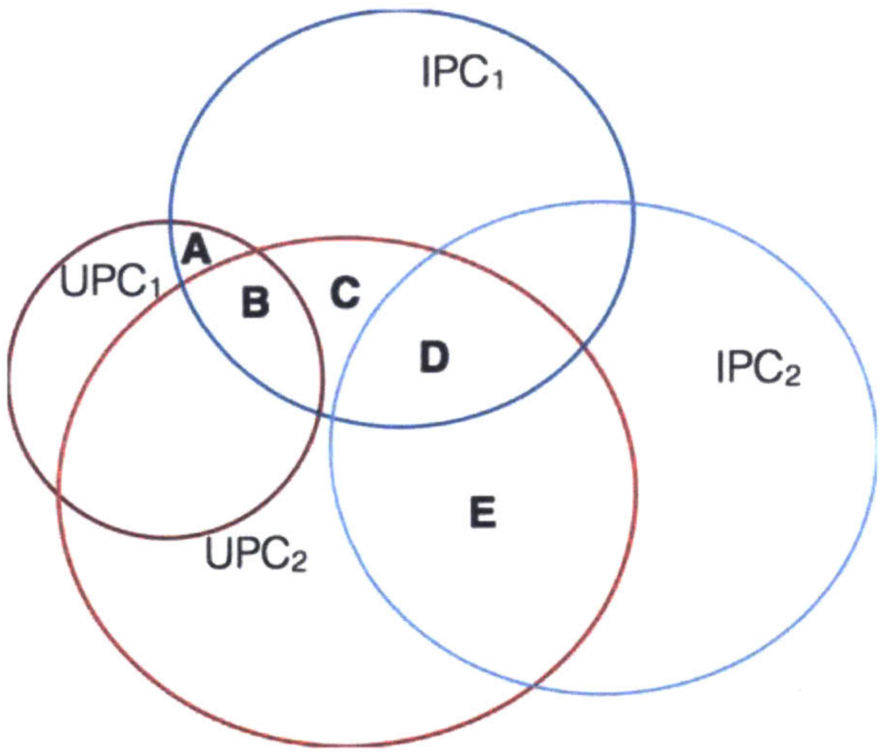

Fig. 2.20: Different types of possible overlaps between multiple IPCs and UPC with specific sectors. Adapted from Benson 2014.

The patent sets with the highest relevancy found in step 4 are examined for completeness in step 5. One gets an idea of completeness by varying the search terms and checking classes with slightly lower MPR. As a final step, the patent set with high relevancy and completeness is chosen as representing the technological domain. Benson and Magee (2015a) have shown that COM retrieves relevant patents consistently (Fig. 2.21) in comparison to methods based on purely keyword or classifications alone.

The COM technique for some domains requires multiple trials to obtain the most relevant and complete set of patents. It might also be necessary to narrow the search by considering the subclasses to obtain a higher percentage of relevant patents, or use Boolean operations with multiple classes to obtain a more complete set.

Field of Interest	COM	Keyword	Classification Selection (UPC)
Photovoltaic Electricity	5101 (85%)	1006 (75%)	7233 (57%)
Wind Turbine	1346 (94%)	1843 (91%)	12893 (26%)
Electric Capacitor	6173 (84%)	11026 (43%)	9472 (2%)
Electrochemical Battery	22115 (62%)	1159 (87%)	26111 (62%)
Computed Tomography	3827 (91%)	1289 (98%)	10444 (69%)

Fig. 2.21: Comparison of size and relevancy of patent sets for 5 domains using three different techniques. Adapted from Benson 2014.

2.4.4 Use of most-cited patents to study technological change

What sample of patents for a technological domains should be used for studying technical change? What should be the basis for selecting the sample? Patents, as a proxy for inventions, have been used for several decades now. Some early quantitative work relating patents to economic variables (Schmookler 1966, Griliches 1984, Trajtenberg 1990) has shown that simple patent count (SPC) of a firm or industry is closely related to their R&D expenditures, an aspect associated with the input side of their innovative processes. The attempt to relate SPC to technological or economic value had been unsuccessful (Griliches et al. 1988). This was due to the fact that SPC assumed that all patent had the same value of 1, and yet in reality they exhibited a huge variation, following a Pareto-like distributions (Scherer 1965). Borrowing the idea of citations being good indicators of the quality of scientific publications (Price 1963), Trajtenberg (1990) studied Computer Tomography (CT) scanners using citations-weighted patent count as a measure of the economic value of patents. He found that citations-weighted patent count were highly correlated to independently calculated economic value of CT scanners. This study established that patent citations were a valuable data source for studying technical change, and since its publication, many research studies have utilized patents and their citations as a variable to study different aspects of invention process, such as spillover (Rosenberg 1982, Nemet and Johnson 2012). Following this understanding and that of others, Benson and Magee (2015b) more recently used bibliographic data (metadata) to construct patent characteristics for 28 technological domains. Among many interesting correlations they have identified between patent metrics and improvement rates of domains, one shows that average number of citations received by patents in a domain in a 3-year period after their issue date are highly correlated with the domains' improvement rates, further providing support to the idea of citations being linked to technological and economic value. Following this tradition, this thesis also utilizes the most-cited patents for studying domain interactions.

2.4.5 Patent content analysis

2.4.5.1 Overview of patent analysis techniques

Patent analysis for technological change research is typically an analytics problem, in which a large amount of data is analyzed to find patterns. With respect to patents, two broad types of patent analysis approaches have been reported in the literature: one based on patent bibliographic data (metadata) and the other on content. Many scholars (Schmookler 1966, Griliches 1984, Trajtenberg 1990, Benson and Magee 2015b) have utilized the first one, patent bibliographic data, to study technological change, whose work was referred in the previous sections. This approach examines macro and meso-level technological trends, but cannot find specific design features in inventions (Yoon and Park 2004).

The second approach, in contrast, utilizes the textual contents of patents - abstract, background, summary, detailed description, and claims - to study technologies. The content-based approach has the potential to detect specific 'technologically significant patterns, trends, and opportunities' (Tseng et al. 2007, Lee et al 2008, Park et al. 2013,).

2.4.5.2 Content analysis techniques based on expert knowledge

Researchers have used several approaches for content analysis. One simple and common approach is the keyword-based analysis. This method requires analysis and identification of specific keywords. The count of the pre-defined keywords or co-occurrences of such words in patents or groups of patents is used for analytical purposes. This has been used by many researchers to identify new technological opportunities from patent maps (Lee et al. 2009), to forecast new technological concepts (Yoon & Park, 2005), and to develop technology roadmaps (Lee et. al 2009; Yoon et al. 2008). The information keyword count can be further processed to identify similarities between patents using cosine measures and Euclidean distance and build technology maps (Salton et al. 1975, Park et al. 2013). One significant disadvantage of this technique is that it does require expert knowledge for identifying the keywords pertinent to the topics in question. Its greatest strength lies in its simplicity, ease of use, and its ability to detect keywords even if their occurrence is low.

Another approach that has been explored is the subject-action-object (SAO) method, in which grammatical structures representing subject (S), verb (representing an action) and object are extracted from sentences from patent content (Cascini et al. 2004) using natural language processing techniques. The resulting data provides insights about the nature and know-how about the inventions (Bergmann et al. 2008, Moehrle et al. 2005), and can be used to construct patent networks and maps utilizing semantic similarities. Park et al. (2013) have proposed an architecture for this technique to construct patent network and maps, and tested it against carbon nanotube technology as a case study. Since this method is potentially powerful, but requires advanced natural language tools (parsers, semantic detectors) to make it execute well, the technique should only be applied where its benefit over use of keywords is clear. It has to be noted that both the keyword and the SAO methods require expert knowledge and supervision.

2.4.5.3 Content analysis techniques requiring no expert knowledge

A number of analytical techniques that do not require expert knowledge have been developed, of which two prominent techniques are Latent Semantic Analysis (LSA) and

Latent Dirichlet Analysis (LDA). LSA is a state-of-the-art natural language processing tool, developed for information retrieval and topic grouping (Griffiths et al. 2007, Broniatowski and Magee 2012). It involves constructing a co-occurrence matrix X = [m x n], whose columns (n) represent the documents (in the full set of documents or corpus D) and rows (m) represent types of words across all the patents. See Fig. 2.22. The entries in the matrix, which function as weights, are the frequencies of each unique word in each patent. Using singular value decomposition, a linear algebra procedure, the matrix X, generally with large dimensions, is reduced to the most significant vectors using the equation: $\mathbf{X = U\ D\ V^T}$ (see Figure 2.23). The first matrix **U** is a set of singular unit vectors of words, whereas **V** is set of mutually orthogonal singular unit vectors of documents. **D** is a diagonal matrix of non-negative singular values, with each value representing a linear combination of weights associated with each singular vector.

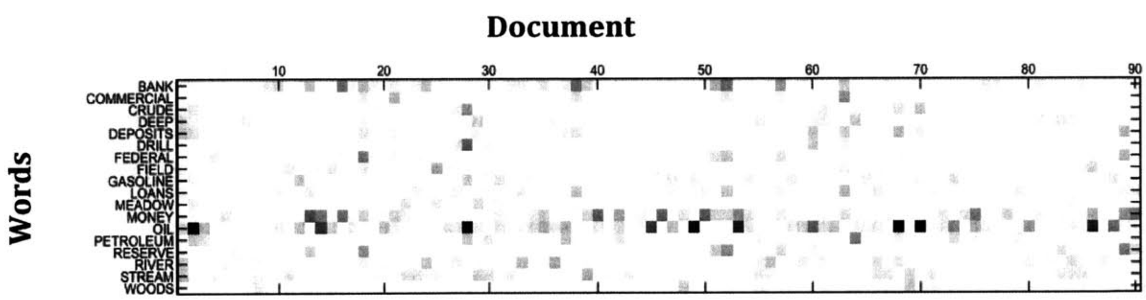

Figure 2.22 A word-document co-occurrence matrix, indicating the frequencies of 18 words across 90 documents extracted from the Touchstone Applied Science Associates corpus. Grayscale indicates the frequency with black being the highest frequency and white being zero. (Adapted from Griffiths et al. 2007 pp 215)

The theory behind LSA asserts that it analyzes all the text by looking at the whole range of words in all the documents, and patterns will emerge in terms of word choice as well as word and document meanings (Dong 2005). This ability makes it potentially suitable for analyzing interactions using patents. This possibility has been demonstrated by LSA's successful use in gleaning shared understanding of design teams (Hill et al. 2001), assessing student essays (Landauer et al. 1998) and retrieving contextual meanings from documents (Deerwester et al. 1990, Foltz 1998). However, progeny and other factors limit its actual usefulness in many cases.

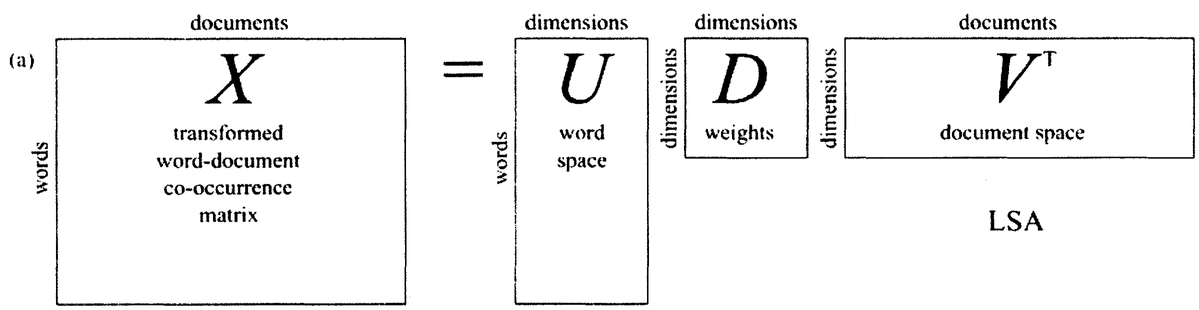

Fig. 2.23: Latent semantic analysis (LSA) performs dimensionality reduction using the singular value decomposition. The transformed word–document co-occurrence matrix, X, is factorized into three smaller matrices, U, D, and V. U provides an orthonormal basis for a spatial representation of words, D weights those dimensions, and V provides an orthonormal basis for a spatial representation of documents. (Excerpt from Griffiths et al. 2007 pp 215)

Latent Dirichlet Analysis (LDA), also known as topic modeling, is an alternative theory and tool for text analysis. It is based on a generative probabilistic model, and uses statistical inference techniques to retrieve latent meaning of words from a stream of topics (Griffith, 2007, Dong et al. 2004, Dong 2005, Broniatowski and Magee 2012). The basic concept is that documents (e. g., patents) are modeled as a random mixture of latent topics, where each topic is characterized by a distribution over the words. The input to the LDA analysis is a word-document co-occurrence matrix, same as the one for LSA (see Fig. 2.22).

LDA reduces the dimensions of the co-occurrence matrix, representing a probability distribution of documents over words, by decomposing into two smaller matrices: a) probability distributions of topics over words, b) probability distributions of documents over topics. Each column of the first matrix represents a topic (see Fig. 2.24) and words in each column are listed in descending order according to their associated probability values. For example, Fig. 2.25 shows the results from a LDA analysis, in which column 1 related to the topic of printing, and column 2 to plays.

Both LSA and topic modeling start with the word-document co-occurrence matrix, and utilize dimensionality reduction techniques. Both provide a gist of the documents, represented as a point in semantic space in LSA and distribution over topics in LDA. A major difference between the two is that the latter is based on a generative model, the former not. As a result, LSA represents meaning of words only 'as points in an undifferentiated Euclidean space'; while LDA provides 'a set of individually meaningful topics and information about which words belong to those topics' (Griffiths et al. 2007). Although both LSA and LDA can indicate the broad topics being discussed in the corpus being analyzed, it is not clear from work reported so far whether these techniques can identify the specific sub-themes being described sparsely in the corpus.

This chapter discussed the background literature salient to answer the research questions presented in chapter 1. The chapter provided a survey of technological change literature, ending with a brief summary of the empirically observed performance improvement in 28 domains. The chapter then discussed design literature (and provided a survey of existing modeling approaches) relevant for developing a quantitative predictive model for explaining the observed exponential performance improvement with variation in improvement rates. The chapter finally discussed the literature relevant for empirical study of component interactions, one of the factors predicted to be potentially responsible for causing variation in improvement rates, using text mining of patents. Next chapter, Chapter 3, presents a theoretical model, methodology and results from an empirical study of component interactions using patents, and finally results from a case study of performance improvement of permanent magnets.

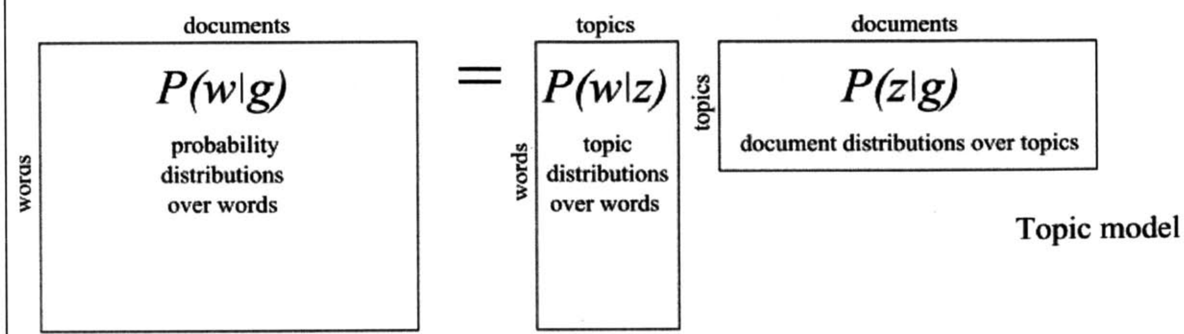

Fig. 2.24: LDA performs dimensionality reduction using statistical inference. The probability distribution over words for each document in the corpus conditioned on its gist, P(w|g), is decomposed into probability distributions over words, P(w|z), where the weights for each document are probability distributions over topics, P(z|g), determined by the gist of the document, g. (Excerpt from Griffiths et al. 2007 pp 215)

PRINTING	**PLAY**	TEAM	JUDGE	HYPOTHESIS	STUDY	**CLASS**	ENGINE
PAPER	PLAYS	GAME	TRIAL	EXPERIMENT	**TEST**	MARX	FUEL
PRINT	STAGE	BASKETBALL	**COURT**	SCIENTIFIC	STUDYING	ECONOMIC	ENGINES
PRINTED	AUDIENCE	PLAYERS	CASE	OBSERVATIONS	HOMEWORK	CAPITALISM	STEAM
TYPE	THEATER	PLAYER	JURY	SCIENTISTS	NEED	CAPITALIST	GASOLINE
PROCESS	ACTORS	**PLAY**	ACCUSED	EXPERIMENTS	**CLASS**	SOCIALIST	AIR
INK	DRAMA	PLAYING	GUILTY	SCIENTIST	MATH	SOCIETY	**POWER**
PRESS	SHAKESPEARE	SOCCER	DEFENDANT	EXPERIMENTAL	TRY	SYSTEM	COMBUSTION
IMAGE	ACTOR	PLAYED	JUSTICE	**TEST**	TEACHER	**POWER**	DIESEL
PRINTER	THEATRE	BALL	**EVIDENCE**	METHOD	WRITE	RULING	EXHAUST
PRINTS	PLAYWRIGHT	TEAMS	WITNESSES	HYPOTHESES	PLAN	SOCIALISM	MIXTURE
PRINTERS	PERFORMANCE	BASKET	CRIME	TESTED	ARITHMETIC	HISTORY	GASES
COPY	DRAMATIC	FOOTBALL	LAWYER	**EVIDENCE**	ASSIGNMENT	POLITICAL	CARBURETOR
COPIES	COSTUMES	SCORE	WITNESS	BASED	PLACE	SOCIAL	GAS
FORM	COMEDY	**COURT**	ATTORNEY	OBSERVATION	STUDIED	STRUGGLE	COMPRESSION
OFFSET	TRAGEDY	GAMES	HEARING	SCIENCE	CAREFULLY	REVOLUTION	JET
GRAPHIC	**CHARACTERS**	TRY	INNOCENT	FACTS	DECIDE	WORKING	BURNING
SURFACE	SCENES	COACH	DEFENSE	DATA	IMPORTANT	PRODUCTION	AUTOMOBILE
PRODUCED	OPERA	GYM	CHARGE	RESULTS	NOTEBOOK	CLASSES	STROKE
CHARACTERS	PERFORMED	SHOT	CRIMINAL	EXPLANATION	REVIEW	BOURGEOIS	INTERNAL

Figure 2.25 Example results from LDA analysis. Each column contains the 20 highest probability words in a single topic, as indicated by P(w|z). These topics were discovered in a completely unsupervised fashion, using just word-document co-occurrence frequencies. (Excerpt from Griffiths et al. 2007 pp 219)

Chapter 3: Methodology and Results

This chapter presents three sets of results. The first set describes development of an explanatory model of technological performance change, the primary output of this thesis. The final model developed identifies two domain parameters – interaction and scaling – that lead to variation in performance improvement among domains. The second set of results tests the interaction parameter empirically to investigate whether, as predicted by the model, it is indeed a factor that can lead to variation in improvement rates. This set is preceded by a methodology section. The final set presents results from a case study of permanent magnet materials, which again tests two predictive empirical models and also expands the empirical context for the modeling effort at the core of the thesis.

3.1 Results - Development of a theoretical model

3.1.1 Introduction

The model presented in this thesis starts with defining the variables, specifying the domain, building internally consistent relationships, and ends by making specific predictions. In section 2.1.4.4, we discussed the pertinent variables (or terms) and technological domains: technological domains as units of analysis, performance metrics and their trends, rates of improvement, operating ideas, interaction, and scaling. Other new terms or variables necessary will be introduced as we present the model. First we present a conceptual model to qualitatively describe the salient elements and how they come together to explain the exponential trends and the variation in rates.

3.1.2 Conceptual basis of model

The model presented here utilizes two sets of mechanisms: the first set explains the genesis of exponential trends, a common feature of all domains; the second set of mechanisms modulate the underlying rate to produce variation in improvement rates across domains. A distinction between the two sets of mechanisms is created by differentiating the idea (or conceptual) regime from the artifact regime. Building upon the understanding of analogical transfer as being more effective in the idea regime (Weisberg 2006), new ideas are viewed as arising from probabilistic combinations of existing ideas. Thus, we model both invention and understanding as probabilistic combinatorial processes building on past ideas and we allow exchanges between the two that eliminate roadblocks following the thinking of Price and others (Price 1983, Gribbin 2002). In the artifact regime, where variation of rates arise, we model the absorption of new inventions into artifacts utilizing the interaction model of McNerney et al. (2011). We use the most popular description of performance changes as a function of design variables (a power law) to model this possible difference among domains.

The overall architecture of the model is shown in Figure 3.1. Based on the work of Vincenti (1990) and Mokyr (2002) discussed in section 2.2.2.3, we separately consider knowledge in the understanding and the operations regimes. We further split the operations regime into idea and artifact sub-regimes. In the idea sub-regime, represented as an IOI "pool" in the figure, designers/inventors work with individual operating ideas (IOI), and combine them to potentially (probabilistic) create new IOI representing new inventions. The IOI concept is a generalization of the operating principle introduced by Polyani (1962) and includes any ideas, including operating principles, invention claims, design structures, component integration tricks, trade secrets and other design knowledge that lead to performance improvement of artifacts. Unlike artifacts, which belong to a specific technological domain, we model IOI in the operations regime as being non-domain specific and available to all technological domains. For instance, the operating principle of total internal reflection is utilized in fiber optic telecommunications, fluorescent microscopy, and fingerprinting, very distinct technological domains. Once new IOI are successfully created through probabilistic combination, they become part of the IOI pool, thus enlarging its size.

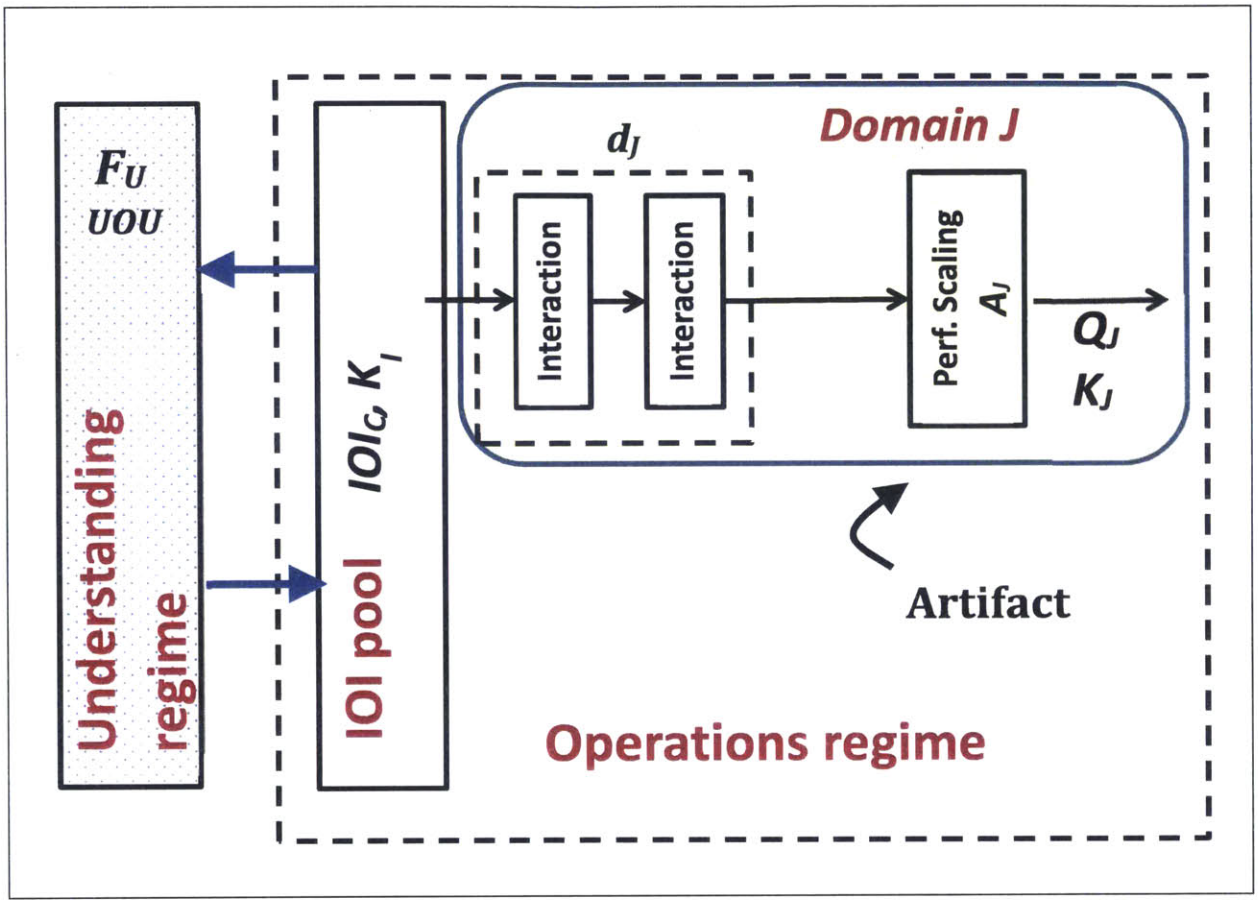

Fig. 3.1: Model of exchange between Understanding and Operation regimes and modulation of IOI assimilation by interaction (d_J) and scaling (A_J) parameters of domain *J*. Arrows between Understanding and Operations regimes indicate the mutual exchange between the two: Understanding regime provides scientific insight to Operations regime, and Operations regime provides operational tools for scientific enquiry. In the Operations regime, each domain assimilates ideas from the IOI pool by resolving interactions between components of a domain artifact. The relative impact of assimilated ideas on performance is dependent on scaling of design parameters governed by the physics of the artifact.

We model growth in the explanatory reach of the Understanding regime by simulating a similar combinatorial analogical transfer process. The Understanding regime is conceptualized to consist of units of understanding (UOU). The units of understanding (UOU) from different fields within the Understanding regime participate to create a new unit of understanding (UOU) that potentially (probabilistically) has a greater level of explanatory and predictive power. Following the treatment in Axtell et al. (2013), we model the explanatory and predictive power of a field of Understanding as a fitness parameter, f_i. If the new UOU has a greater fitness value, it replaces the UOU with the smallest fitness value. Since our primary focus is on performance, output of the Operations regime, we simulate the Understanding regime only at this higher abstraction level.

Although both regimes - understanding and operations - evolve independently, they cannot do so indefinitely. We model the de Solla Price (1983) insight by having each regime act as a "barrier-breaker" for the other regime through mutual exchange (depicted by the arrows between the regimes in Fig. 3.1). When each regime hits a barrier, the other can eventually aid in breaking the barrier: infusion of understanding enables creation of important IOI in the operations regime; and infusion of new operational measurement/observation tools enable new discovery in the understanding regime.

The performances of the technological domains, which reside in the artifact sub-regime, are improved by a series of designs/inventions over time. The series of inventions are based upon each domain receiving IOI from the pool. IOI enable specific components in the domain artifact to effect change in the component leading to an improvement. Following McNerney et al.'s treatment, whether the component is able to absorb an IOI depends upon the average number of component interactions d_J in the domain J, which is defined as the average number of components a specific component influences, including itself. In order to accommodate the change in the IOI-assimilating component, other components also change. The IOI in question is assimilated only if the performance of the artifact overall improves. The McNerney et al. model (and our adaptation of it) predict that more interactions make it harder for a component to assimilate an IOI. In short, the higher the number of problems to solve, the harder it gets to assimilate an operating idea.

Another, and final, factor that we model is scaling, a property inherent in the physics of the artifact[17]. The successfully assimilated IOI, which we refer to as IOI_S, effect improvement of the domain artifact by enabling favorable change of a relevant design parameter. The design parameter is increased or decreased such that it leads to improved performance. Scaling refers to how change in a design parameter relates to changes in the performance of an artifact. One ubiquitous design parameter is geometry, which enters in the form of length, area, or volume. Taguchi (1992) noted that some phenomena tend to work better when carried out at a smaller scale ("smaller is better"), while other are better at larger scale ("larger is better"). Integrated circuits, for example, perform better as dimensions are reduced, since smaller dimensions lead to shorter delays, and higher density of transistors, both of which contribute towards improved computation per volume or cost. The formulation we use in the model is that relative performance change is related to design parameters raised to some power, in other words scaled. As covered in literature review section 2.2.5 on scaling, this is the most widely used functional relationship with decent empirical support and theoretical justification in some cases (Barenblatt 1996).

3.1.3 Mathematical model

3.1.3.1 Summary

A performance (intensive) metric of a domain, labeled Q_J, is a function of a set of design parameters (s_1, s_2, s_3) of a domain artifact and time but for simplicity here we consider only a single design parameter s. The design parameter s is changed by $IOIsc$ (successfully assimilated IOI into domain artifacts), which in turn are assimilated from IOI_C (number of accumulated operating ideas in the IOI pool shown in Figure 2). IOI_C is a function of time. Considering a single design parameter s for simplicity, for a domain J, this sequential functional dependency ($Q_J \leftarrow s \leftarrow IOI_{SC} \leftarrow IOI_C \leftarrow t$) can be expressed mathematically as:

$$Q_J = f_1(s); \quad s = f_2(IOI_{SC}); \quad IOI_{SC} = f_3(IOI_C); \quad IOI_C = f_4(t) \qquad (3.3a)$$

[17] Recall that the performance we consider in this paper is intensive, e.g., energy density, w/cm3. In relations to artifacts such as software, physics refers to the mathematics behind the software.

Where IOI_{SC}, IOI_C are respectively cumulative number of $IOIs$ (in domain J), and *IOI in the* Ideas pool. Note that Q_J, s, IOI_{SC}, IOI_C are all functions of time.

Since $d\ ln\ Q_J/dt$ (the exponential rate of improvement in performance) is what we want to find from the model, the form of most use for our research question is the logarithmic derivative. Consequently, we work with the logarithm of each quantity (with necessary changes in the functional relationships), resulting in the following new relationships.

$$ln\ Q_J = f_1'(ln\ s);\quad ln\ s = f_2'(ln\ IOI_{SC});\quad ln\ IOI_{SC} = f_3'(ln\ IOI_C);\quad ln\ IOI_C = f_4'(t) \tag{3.4b}$$

The sequential dependency ($ln\ Q \leftarrow ln\ s \leftarrow ln\ IOI_{SC} \leftarrow ln\ IOI_C \leftarrow t$) implies that the time derivative of $ln\ Q$ can be decomposed as follows using the standard chain rule from differential calculus:

$$d\ lnQ_J/dt = d\ lnQ_J/d\ lns \cdot d\ lns/d\ lnIOI_{SC} \cdot d\ lnIOI_{SC}/d\ lnIOI_C \cdot d\ lnIOI_C/dt \tag{3.5}$$

Where, the first term on the right hand side represents the scaling parameter (A_J) assuming that Q_J is a power law in s: $d\ lnQ_J/d\ lns = A_J$. The second term is the 'smaller-is-better/larger-is-better' factor, and captures the notion whether design variable has to be increased or decreased in order to improve performance. We capture this dependence using an abstraction and equate $d\ lns/d\ lnIOIsc = +/-1$. The equation now reduces to:

$$d\ lnQ_J/dt = A_J \cdot (\pm 1) \cdot d\ lnIOI_{SC}/dlnIOI_C \cdot d\ lnIOI_C/dt \tag{3.6}$$

The next aspect of the model is to relate the domain specific successful IOI_{SC} to the IOI_C in the pool: which we will show - following McNerney et al. - as $d\ lnIOI_{SC}/d\ lnIOI_C = 1/d_J$, where d_J is the interaction parameter introduced by McNerney et al. Finally, the fourth term is the time dependence of the number of $IOIc$, represented by K_I. With this, and representing $K_J = d\ lnQ_J/dt$, equation 3.3 as a whole reduces to:

$$K_J = (\pm 1) \cdot A_J \cdot 1/d_J \cdot K_I \qquad \text{(3.28 preview)}$$

In the subsequent sections, we present derivations for the second and third terms on the right hand side of the above equation. However, we start with $K_I = d\ lnIOI_C/dt$, which is arrived by a simulation of combinatorial analogical transfer.

3.1.3.2 Overall IOI simulation - genesis of exponential trends

As noted in the conceptual model in section 3.1.2, we model the IOI as resulting from combining knowledge from prior IOI by probabilistic combinatorial analogical transfer. Fig. 3.2a schematically represents combination of IOI, in which specific IOI *a* and *b* combine to create IOI *d* with a probability, P_{IOI}. If this combination attempt succeeds, the newly created IOI *d* then is added to the pool of IOI (Fig 3.2b). In subsequent time steps, IOI *d* can attempt to combine with another specific IOI in the pool, such as IOI *c*, to probabilistically create a more advanced IOI *e* (Fig. 3.2a). As this process of combination proceeds, the cumulative number of individual operating ideas, IOI_C grows. We further make the distinction between derived IOI and basic IOI, the latter we label as IOI_0. IOI_0 are fundamental IOI, which first introduce a natural effect into an operational principle to achieve some purpose. A pair of close parallel surfaces in a dense medium, like in a fiber optic cable, which make it possible to send a beam of light using the phenomenon of total internal reflection can be viewed as an example of an IOI_0. In contrast, derived IOI, just as the term suggests, are obtained through combination of two IOI_0, or between an IOI_0 and a derived IOI or betwee[18]n two derived IOI. In this sense, IOI *a*, *b*, and *c* in the figure represent IOI_0 and IOI *d* and *e*, derived IOI.

In one run of the simulation, we start with the initial number of basic individual operating ideas, IOI_0. At each time step, we allow combinations equal to half the number of total IOI available at given time step to be created. Fig. 3.3 shows results from a simulation run starting with 10 basic IOI and a probability of combination, P_{IOI}, equal to 0.25. With time steps on the X-axis and the cumulative number of operating ideas, IOI_C on the Y-axis, Fig 3.3 *a* and *b* show that the cumulative number of operating ideas, IOI_C, grows exponentially with time at a growth rate (K_I) of 0.116 for this particular run.

[18] The intention is to allow *each* operating idea to combine with another operating idea *once* per time step on average.

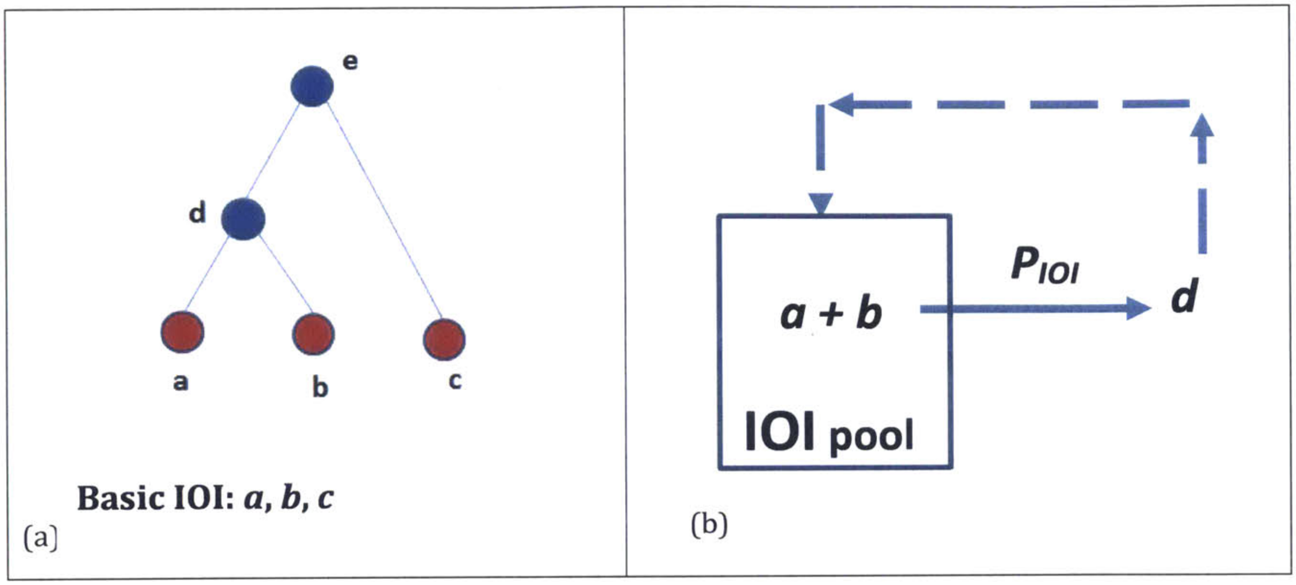

Fig. 3.2: Recombination of individual operating ideas a) basic and derived IOI b) accumulation of IOI through feedback

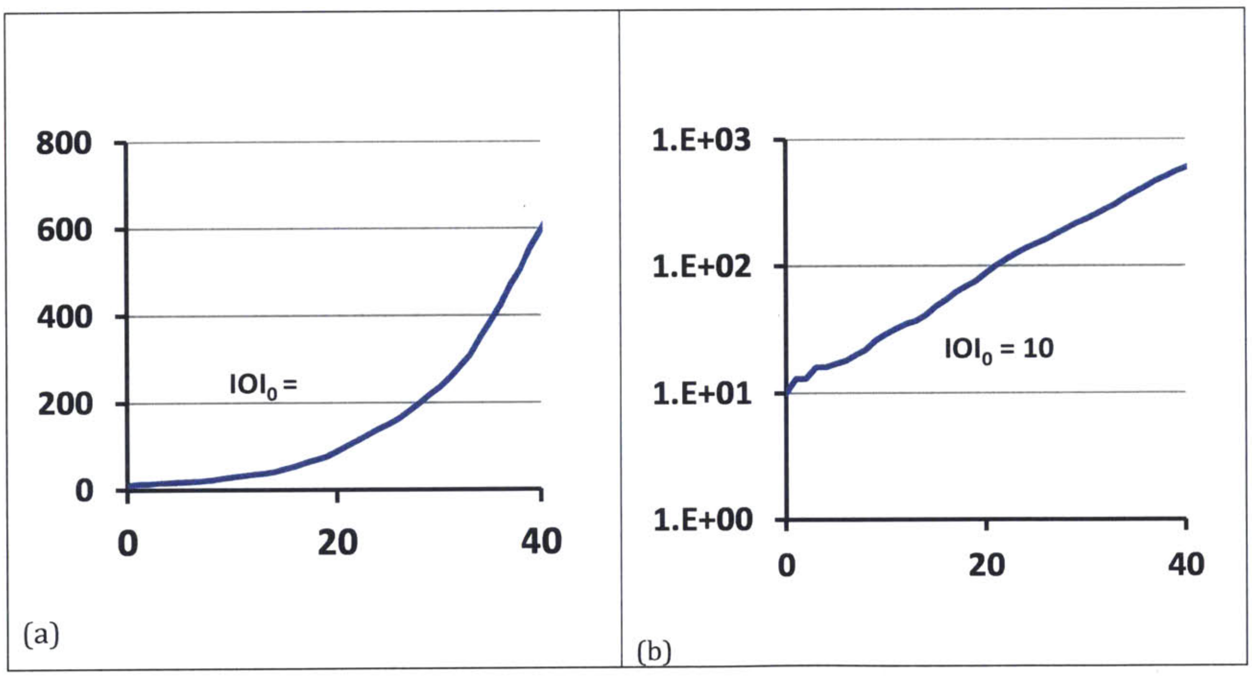

Fig. 3.3: Growth of IOI_C over time: initial IOI_0 = 10, probability of recombination, P_{IOI} = 0.25: (a) linear Y-axis (b) logarithmic Y-axis.

For this simplified case, K_I, the rate of growth of IOI, can be mathematically shown to be equal to $ln(1 + P_{IOI}/2) = 0.118$ which can be easily derived as follows:

At time step t, number of new IOIs created = $P_{IOI} \cdot IOIc(t)/2$ (3.7)

The number of IOI at the next time step, t+1 is given by:

$IOIc(t+1) = IOIc(t) + P_{IOI} \cdot IOIc(t)/2 = IOIc(t) \cdot (1 + P_{IOI}/2)$ (3.8)

Ratio of $IOIc$ between consecutive time steps, $r = IOIc(t+1)/IOIc(t) = (1 + P_{IOI}/2)$ (3.9)

Since the ratio is a constant, we can view $IOIsc$ at each time step as terms in a geometric series. Thus, in general, $IOI_c(t)$ can be written in terms of an initial IOI_0 and ratio, r and time step, t; the expression can be further expressed in an exponential form as follows.

$IOIc(t) = IOI_0 \cdot r^t$ (3.8)

$IOIc(t) = IOI_0 \exp\{lnr \cdot t\} = IOI_0 \cdot \exp\{ln(1 + P_{IOI}/2) \cdot t\} = IOI_0 \cdot \exp\{K_I \cdot t\}$ (3.9)

Where, rate of growth of $IOIc(t)$,

$K_I = ln(1 + P_{IOI}/2)$ (3.10)

For very small values of P_{IOI},

$K_I \approx P_{IOI}/2$ (3.11)

This preliminary model demonstrates the simplicity of finding an exponential relationship. However, the simulation results to this point assume that indefinitely large numbers of operating ideas, IOI, can be created out of few basic IOI. This is because the model assumes that the same operating ideas can be repeatedly used to create new IOI without limit. (For example, recombining (a,b) with a, then with b would give new operating IOI (((a,b),a),b) and eventually an arbitrarily large number of a, b pairs. The assumption that an indefinite number of IOI can be created from a few basic IOI does not appear to be realistic.

In order to better reflect reality, we introduce a constraint that any derived IOI can utilize an IOI_0 only once. The constraint operationalizes the notion that counting repetitious use of basic IOI as new designs is unrealistic. According to this constraint, derived IOI $e = (d, c)$ =

(a, b, c) (in Fig. 3.2a) would be allowed, but not $g = (d, f) = (a, b, b, c)$ (in Fig. 3.4b). Employing this constraint, the simulation results in Fig. 3.5a, a semi-log graph, show the cumulative number of IOI initially growing exponentially with time. However, later on the curve bends over and hits a limit, demonstrating that all combination possibilities have been completely used up, and the pool of operating ideas stagnates which is also shown on the linear plot (Figure 3.5b) resembling a well-known "S-curve".

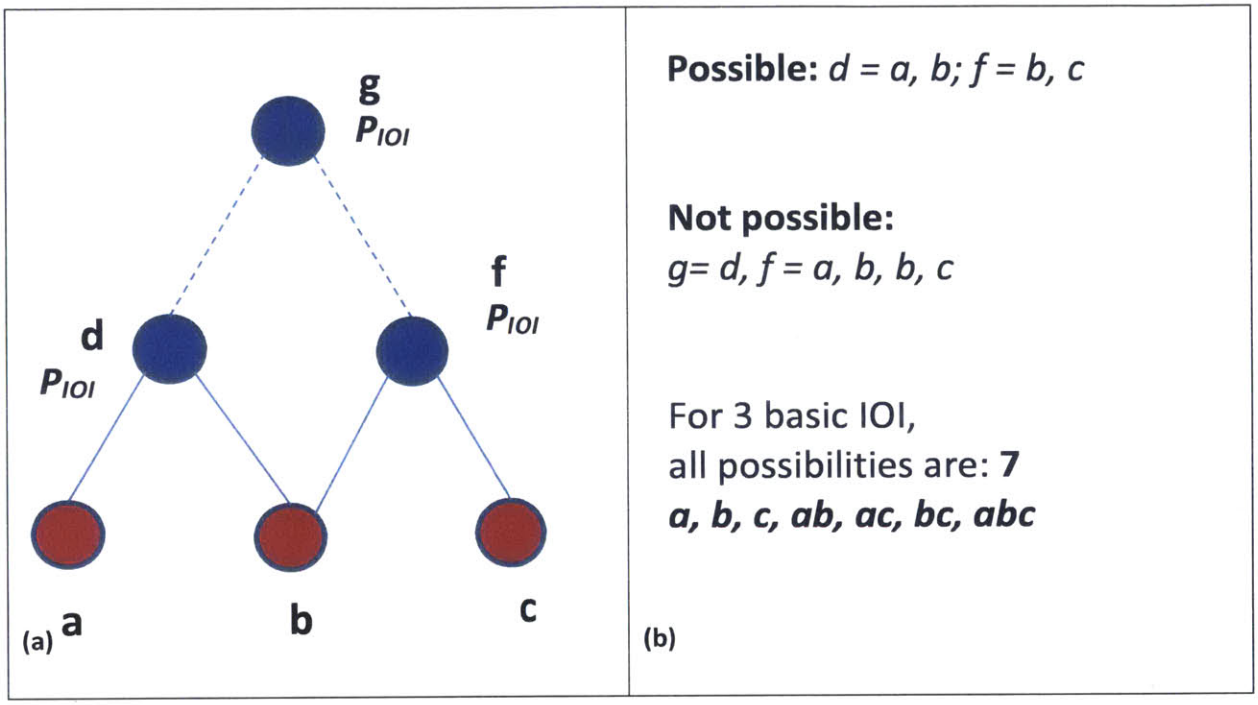

Fig. 3.4: New recombination rule: no basic IOI can be used more than once.

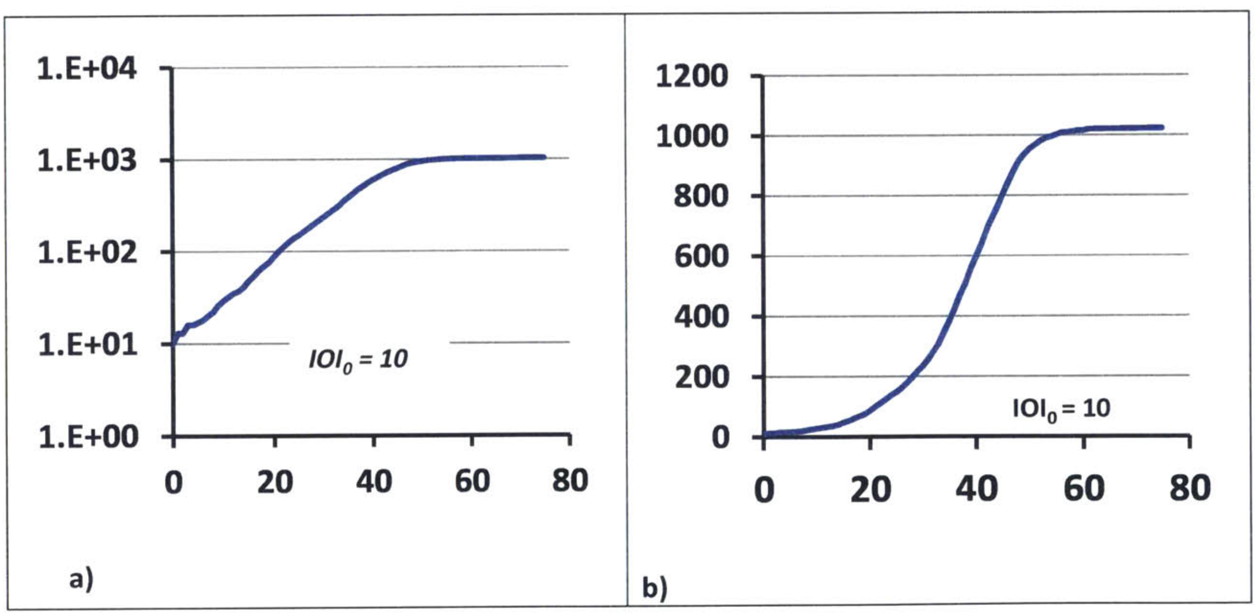

Fig. 3.5: Growth of cumulative *IOIc(t)* after implementing the constraint that IOI_0 can be used only once by any specific derived IOIs; a) semi-log plot and b) linear plot.

The maximum number of combination possibilities, which is a function of IOI_0 in the pool, defines the limit. This limit, or maximum number of combination possibilities, is given by a simple combinatorics equation (Cameron 1995):

$$IOI_{max} = 2^{IOI_0} - 1 \qquad (3.12)$$

This equation entails that the limit increases rapidly as IOI_0 increases, due to its geometric dependence on IOI_0 (Fig. 3.6). For example, for IOI_0 equal to 5, 10, 15, and 20 the corresponding limits are 31, 1023, 32767, and 1,048575 combination possibilities.

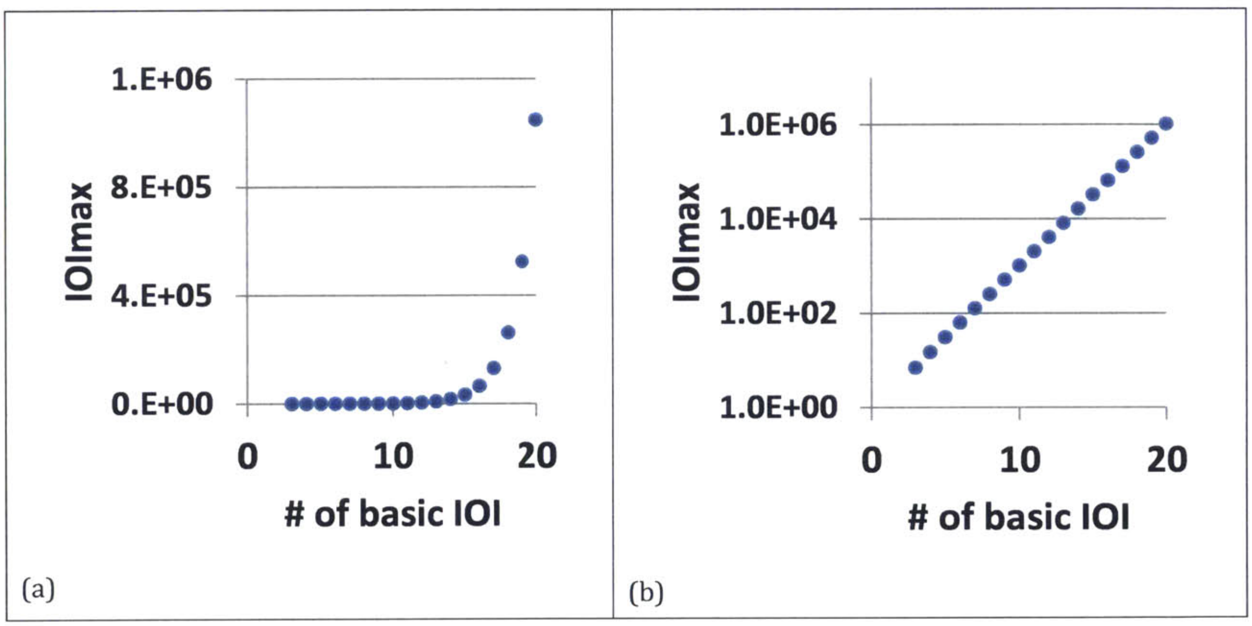

Fig. 3.6 Rapid rise of combinatorial limit: (a) linear-scale (b) log-scale

A natural question that arises from this result is what might determine the IOI_0 over time? We postulate a role for Science or Understanding in this regard but we first briefly look at how Understanding evolves over time.

3.1.3.3 Combinatoric simulations for Understanding

Just like the Operations regime, we model the Understanding regime to also grow through a probabilistic analogical transfer process, in which units of Understanding combine to create new units of Understanding.

In this model, we envision that Understanding is composed of many fields, with each field having an explanatory reach. Using a treatment similar to the one used by Axtell et al. (2013), the explanatory reach of a field may be viewed as a fitness value of the theoretical understanding of that field, which we denote with f_i. When units from two fields with fitness values, f_1 and f_2, combine[19], the fitness of the resulting unit is randomly chosen from a triangular distribution with the base or X-axis denoting the fitness values ranging from 0 to $f_1 + f_2$, and the apex representing the maximum value of the probability distribution function, given by $2/(f_1 + f_2)$. See Fig 3.7a. If the resulting fitness of the new Understanding unit is higher than the fitness of either of the two combining units, the new understanding unit replaces the unit whose fitness is the smallest among the three. We assume the cumulative fitness of the Understanding regime as a whole to be equal to the sum of the individual fitness value of each field.

Our simulation assumes 10 fields with starting fitness values ranging from 0 to 1, which are randomly assigned. Consequently, the cumulative fitness value of Understanding regime averages to a value of 5 initially. As the simulation proceeds, fitness values of the 10 fields grow independently, and as a result, the cumulative fitness of the Understanding regime grows. Fig. 3.7b shows results from a simulation run exhibiting roughly exponential growth of cumulative fitness over time. Thus, the simplest model for growth of the understanding regime is also exponential. However, as with the Operations regime, unlimited growth by simple combination of scientific theories is not realistic.

[19] Since the purpose of this work is to develop a model for the operations regime, the Understanding regime is treated at a higher abstraction level, and specific mechanisms used for combination of UOU are not modeled.

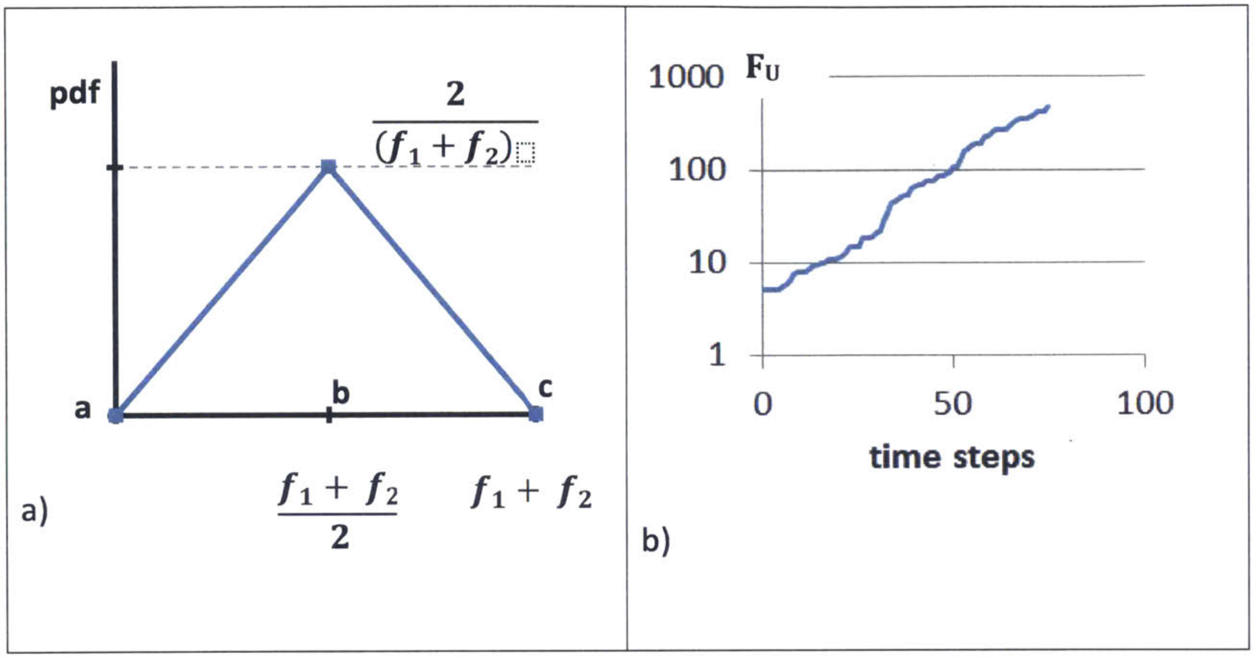

Fig. 3.7: a) Triangular distribution of possible fitness values that can be assumed by a new unit of Understanding b) Growth of F_U (cumulative fitness of Understanding) regime) over time.

The Understanding regime also cannot progress indefinitely by simple combination of existing understanding but instead experiences a limit that we envision as depending upon availability of operational (technological) tools available for testing scientific hypotheses. We express this dependence through an equation which expresses the maximum cumulative fitness at any time, $maxF_U(t)$, as simply proportional to the IOI existing at that time :

$$maxF_{\underline{U}}(t) = Z_F \cdot IOI_C(t) \qquad (3.13)$$

Where IOI_C thus represents an approximation for the effectiveness of available observational tools, and Z_F, a constant of proportionality. This equation captures the concept first suggested by Price that the extent (or scope) of explanatory reach of the understanding regime is dependent upon what operational tools (experimental approaches and tools) are available for scientists and researchers. It also recognizes in the terms of our model that these tools are essentially operational artifacts. The capability to measure accurately increases as the number and quality of available tools increases.

3.1.3.4 Exchanges between science and technology and its impact on exponential trends

The relationship of science and technology, discussed in literature review section 2.2.3, is not well-modeled by a simple linear model, but mutually beneficial relationship, summarized in Fig. 3.8, is consistent with prior qualitative work. In our model, we capture this enabling exchange from the Understanding to the Operations regime using a simple mathematical criterion:

$$F_U(t)/F_U(t\_prev) \geq cutoff\_ratio\ (R) \qquad (3.14)$$

Where, $F_U(t)$ and $F_U(t\_prev)$ represent cumulative fitness values at time step t and the most recent time step, *t_prev*, at which a IOI_0 had been introduced[20].

This criterion states that when cumulative fitness of the Understanding regime grows by some multiple (R) from the time when the last IOI_0 was invented, understanding has improved enough to generate a new IOI_0, which becomes available for combinations with all existing IOI. The threshold ratio, R, determines the frequency at which IOI_0 are created.

[20] Another possible formulation is based on difference:
$F_U(t) - F_U(t\_prev) \geq cut\text{-}off\ difference$

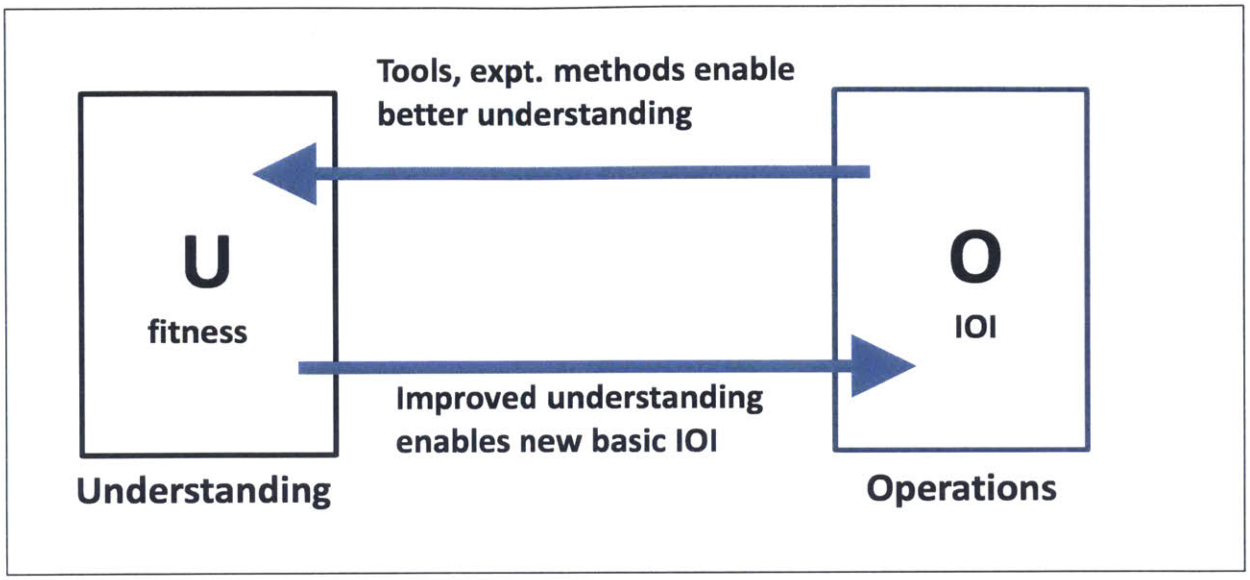

Fig. 3.8 Synergistic exchange between understanding and operations

We now show results from a simulation including the exchange and limits on IOI_0. In the simulation, we study how synergistic exchange from Understanding influences the rate of growth of IOI in the Operations regime, including escape from stagnation. We focus particularly on two variables, namely, the initial number of IOI_0 in the Operations regime and the threshold ratio R for creation of new IOI_0. Other pertinent variables are the probability of combination, P_{IOI}, and the number of combinatorial attempts occurring per year.

For this simulation study, Table (3.1) presents the parameter values for IOI_0 (column 3) and R (column 4) that are used. As an example, 5B3R starts with IOI_0 of 5 and a new IOI_0 is created when cumulative fitness grows by 3 times. Both the initial number of IOI_0 and the threshold ratios of cumulative fitness, R, are set at 3 different values, giving a total set of 9 parameter combinations. For all 9 runs, the value of probability for combination is kept constant at 0.25, and we assume one attempt per yearly time step.

Table 3.1: Simulation study: Parameter values of IOI_0 and R (threshold ratios of cumulative fitness of Understanding) for the study. Results: K_I is the slope fitting the simulation results to an exponential with R^2 for the fit (also shown). Other parameters, such as probability of combination, $P_{IOI} = 0.25$, are kept constant.						
	Simulation Run	**Initial IOI_0**	**Threshold ratio R**	**Simulation K_I (± 2 std dev)**	R^2	$K_I = ln(1+ P_{IOI}/2)$
1	**5B1.5R**	5	1.5	0.123 (± 0.011)	0.998	0.118
2	**5B3R**	5	3.0	0.055 (± 0.019)	0.959	0.118
3	**5B5R**	5	5.0	0.039 (± 0.007)	0.943	0.118
4	**10B1.5R**	10	1.5	0.122 (± 0.011)	0.997	0.118
5	**10B3R**	10	3.0	0.115 (± 0.007)	0.998	0.118
6	**10B5R**	10	5.0	0.117 (± 0.007)	0.983	0.118
7	**20B1.5R**	20	1.5	0.116 (± 0.007)	0.998	0.118
8	**20B3R**	20	3.0	0.116 (± 0.009)	0.998	0.118
9	**20B5R**	20	5.0	0.119 (± 0.016)	0.998	0.118

The simulation results in Fig. 3.9 shows the temporal growth of IOI_C in the Operations regime for the nine runs shown in Table 3.1. Runs 5B3R and 5B5R clearly stand out: they have a bumpy growth since they encounter periods of stagnation multiple times, as they evolve. However, their effective rates of growth are meager, standing only at 0.05 and 0.02, which is much lower than 0.118, the rate given by Equation 3.10 $\{= ln\ (1+ P_{IOI}/2)\}$. Columns 5, 6, and 7 list the K_I, R^2, and K_{I_cal} calculated using $ln(1+ P_{IOI}/2)$ respectively. The small deviations from equation 3.10 found for the other 7 runs are within the 2-sigma estimated from multiple simulation repetitions for each run.

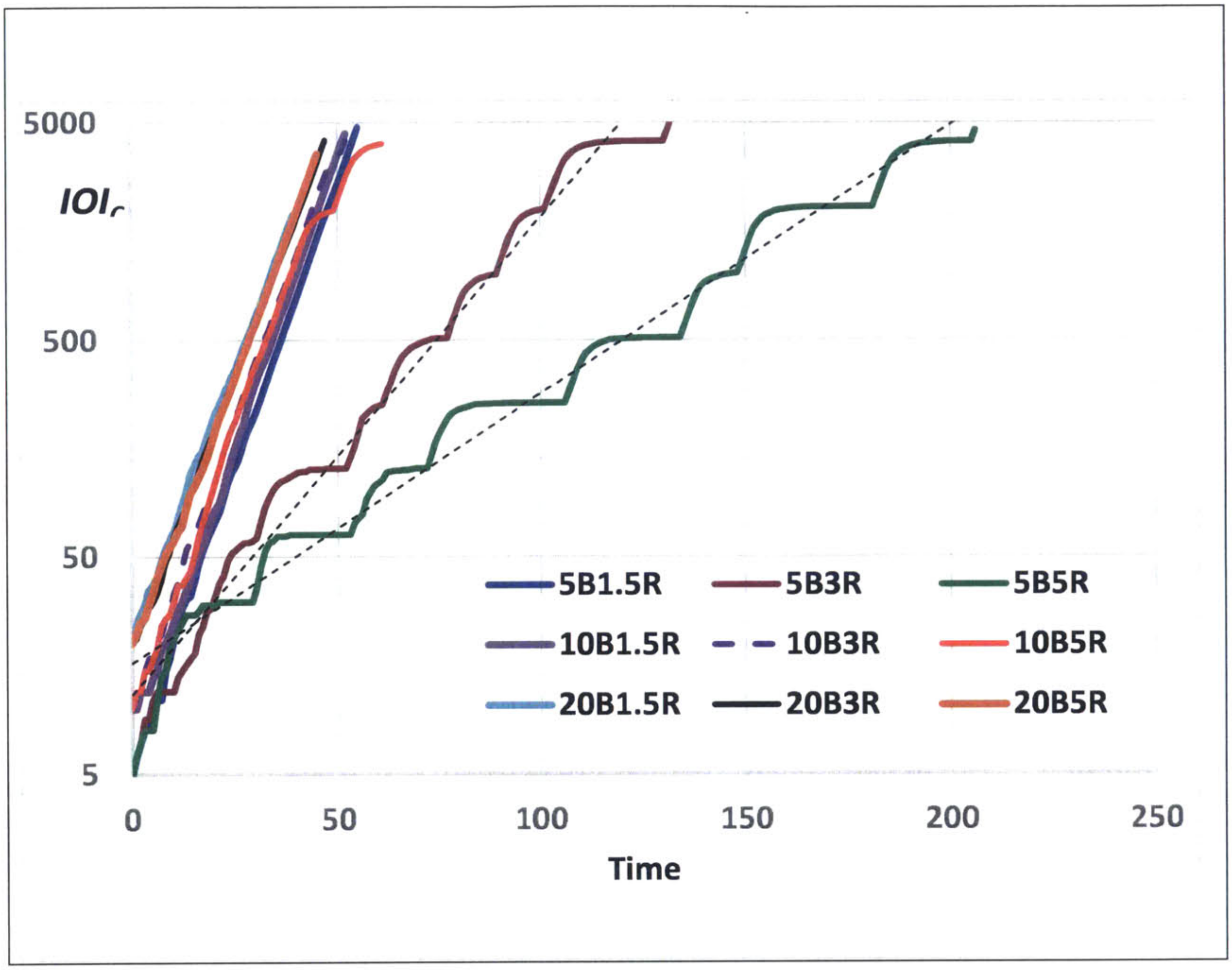

Fig. 3.9: Growth of *IOI_c* over time. Initial *IOI_0* and *R* (cumulative fitness ratio) for each run are shown in the legend for each run; e.g., 10B5R represents 10 *IOI_0* and fitness ratio *R* of 5. Each curve is a representative sample from each run.

Both 5B3R and 5B5R start with low initial *IOI_0* of 5 and have higher cumulative fitness threshold ratios (*R*) for infusion of new IOI_0. Low initial *IOI_0* implies that the Operation regime has a low number of combinatorial possibilities of IOI to start with.

Additionally, since new IOI_0 are not coming fast enough to push the frontier of combinatorial possibilities of IOI far enough, the Operation regime quickly exhausts the possibilities and again stagnates. Run5B5R stagnates for longer periods compared to 5B3R since it has a higher threshold ratio (*R*) for infusion of a new IOI_0 and thus slower progress. The Operation regime cannot escape the stagnation until another IOI_0 is created with infusion of new Understanding. It is clear from the curves that this pattern repeats itself time after time.

Other simulation runs, except run 10B5R grow exponentially and smoothly and their rates are consistent with the theoretical value 0.118 calculated using $ln(1+ P_{IOI} /2)$. These curves have either high enough IOI_0 to start with or fast infusion of IOI_0, or both. Run 5B1.5R, for example, starts with a low number of IOI_0 but has fast infusion of IOI_0, since the threshold ratio *R* is only 1.5. On the other hand, run 20B5R has slow infusion of IOI_0 (high R), but starts with high initial IOI_0.

These runs do not exhibit stagnation for two reasons. The first reason is that the frontier of combinatorial possibilities for some runs is very far from the number of realized IOI at a given time step. For example, run 20B5R has over a million possibilities when it starts with 20 IOI_0. The second reason is that the frontier of the combinatorial possibilities keeps on moving further away as IOI_c increases. Run 5B1.5R, for example, starts with 5 IOI_0, and yet it never experiences stagnation due to fast infusion of IOI_0 (low *R*) that push the frontier of combinatorial possibilities. The growth of IOI_C is also free of stagnation for runs (e.g., such as Run 10B3R) with medium number of initial IOI_0 and medium rate of infusion of IOI_0 (medium *R*). This is true because both factors in combination ensure that frontier of combinatorial possibilities is far enough to start with, and the frontier continues to move rapidly enough with time.

Run 10B5R exhibits somewhat unusual behavior. Although it grows smoothly at the beginning for quite some time, it experiences stagnation later on. This is because the frontier of combinatorial possibilities is far enough away to sustain steady growth early on. Later, the Operation regime exhausts the combinatorial possibilities before new IOI_0 arrive. However, once a new IOI_0 arrives, it jumpstarts again but it briefly halts at each new limit showing the value of frequent interchange between science and technology in this simulation.[21]

We have seen that a combinatorial process augmented with synergistic exchange between Understanding and Operations leads to an exponentially growing pool of operating ideas, IOI_C. This growth is described by an exponential function, and its growth rate is given by time derivative of its logarithm:

$$IOI_C(t) = IOI_0(t_0)\exp\{K_I(t - t_0)\} \qquad (3.15A)$$

$$K_I = \frac{d\ lnIOI_C}{dt} \qquad (3.15B)$$

Where, K_I = the effective rate of growth of IOI_C, $IOI_0(t_0)$ = the number of initial basic IOI, t = time, t_0 = initial time.

Our overall conceptual model (Section 3.1.2, Figure 3.1) envisages that this exponentially growing pool of operating ideas, IOI_C, provides the source for the exponential growth of performance of technological domains. How does this exponential growth of IOI_C result in performance improvement and what accounts for the variation in rates of performance improvement across technological domains?

3.1.3.5 Modeling interaction differences among domains

As explained in literature review sections 2.2.4 and 2.2.5, two factors potentially responsible for modulating the exponential growth of operating ideas as they are integrated into technological domains are the domain interactions and scaling of relevant design variables. We consider domain interactions first and demonstrate how the term

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[21] The simulations are based upon infusion of IOI_0 depending upon a ratio (R) of growth in cumulative understanding, but similar results are found with assuming a model of difference in F_U.

$$d\ lnIOI_{SC}/d\ lnIOI_{SC} = 1/d \qquad \text{(Preview eq. 3.20)}$$

McNerney et al. (2011) have modeled how interactions in processes affect unit cost. We build on their mathematical treatment to analyze the effect of interactions between components upon integrating IOI into artifacts in a domain, which in turn affects the domain's performance improvement. Fig. 3.10 a shows a simplified schematic of an artifact in a technological domain that has three components (1,2,3) with interaction being depicted by out-going arrows, representing influence, from a component to other components, including itself. The outgoing arrows are referred to as out-links. The number of out-links, *d*, from a component provides a measure of its interaction level, and has value of 1 or greater as McNerney et al. assume each component at least affects itself. For simplicity, we show each component with two out-links, to itself and to another component. We represent an instance of an attempt being made to improve the performance of component 2 by an IOI being inserted. Since component 2 interacts with itself and another component, the performance of the interacting component is also changed by the insertion but in a fashion described probabilistically. The performance improvement attempt is accepted, only if the performance of the artifact as a whole improves. If that does occur, we consider the interactions being successfully resolved to improve the performance.

For a simplified artifact with *d* number of out-links for each component (*d*=2 in Fig. 3.10a), McNerney et. al.'s treatment (2011) for unit cost results in the following relationship:

$$dC/dm = - B \cdot C^{d+1} \qquad (3.16)$$

Where, C = unit cost normalized with respect to initial cost[22], m = number of attempts, d= number of out-links, B = constant

[22] The normalized unit cost is 1 or less.

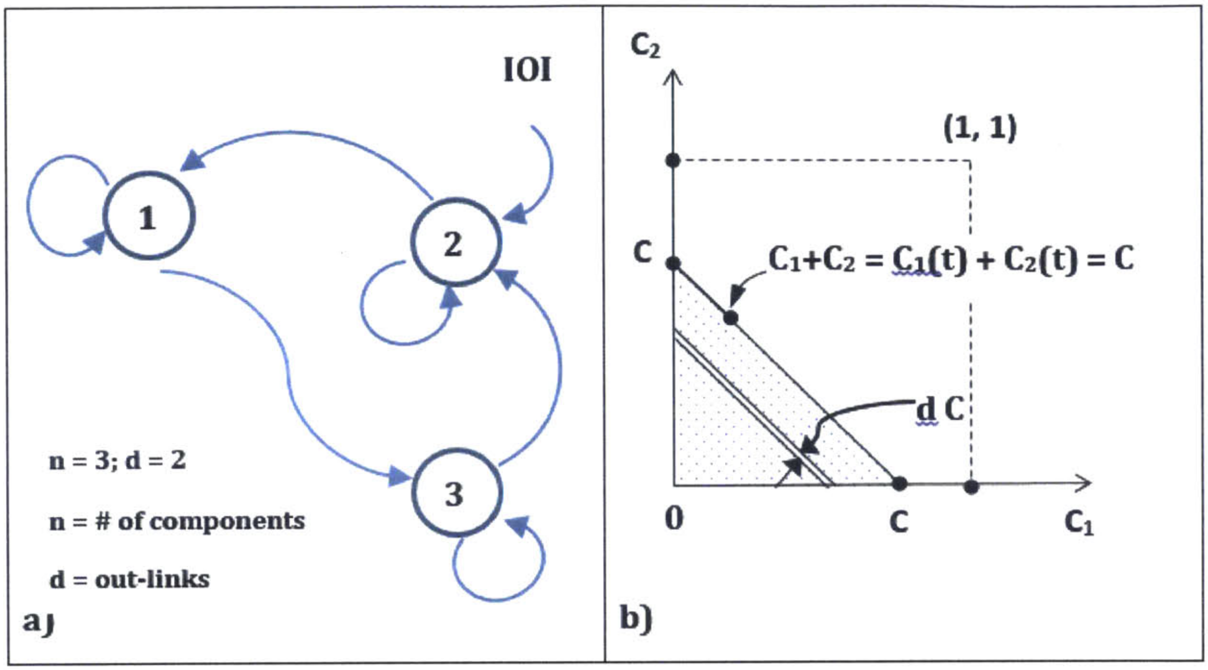


Fig. 3.10: Interactions in an artifact; a) illustration of interactions as out-links b) sample space of probabilities for unit cost in an artifact with two components.

This equation states that the level of interaction inherent in the domain artifact influences the rate of unit cost reduction. We adapt this equation for our analysis in the following manner. We interpret number of attempts as IOI_C since at each attempt an IOI is being introduced into an artifact to make a design change. Secondly, reduction in unit cost can be interpreted as inverse of intensive performance improvement, in which the cost is the resource constraint (such as in a typical metric kWh/\$[23]). With these extensions, equation 3.16 can be re-written as:

$$d(Q)/d\, IOI_c = B \cdot Q^{-(d-1)} \qquad (3.17)$$

Where, Q = performance of a domain

Since as shown in Equations 3.3 and 3.4, successfully resolved operating ideas in a domain, IOI_S, are the source for its performance im provement, we replace performance Q of a domain with IOI_{SC}. An IOI is considered a successful attempt if the interaction

[23] The concept can be further generalized to include performance metrics which involve other resource constraints such as volume, mass, and time (e.g., kwh/m[3]), instead of cost.

resolution leads to net performance improvement of the artifact, and we refer to the successful IOI as a domain IOI, denoted by IOI_S. The modified equation shown below states that interaction level, *d*, has a retarding effect on the growth of IOI_{SC}, cumulative number of IOI_S, in a domain.

$$\frac{d(IOI_{SC})}{dIOI_C} = B \cdot IOI_{SC}^{-(1-d)} \tag{3.18}$$

We solve the differential equation by separating the variables, and integrating both sides using dummy variables, and express IOI_{SC} explicitly. The integration limits are: (a) for the right side, 0 to IOI_C, (b) for the left side, 1 to IOI_{SC}. The result is equation 3.19A. Since *B* and *d* are closer to unity, and $IOIc$ >> 1, we can ignore 1, and simplify the relation to equation 3.19B. :

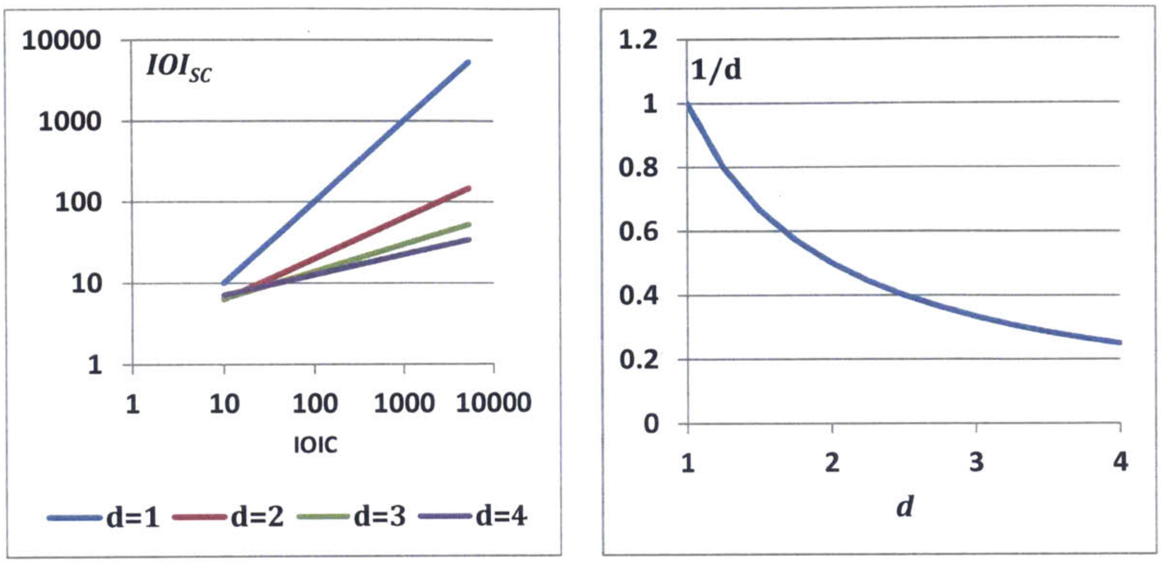
$$IOI_{SC} = (B \cdot d \cdot IOI_C + 1)^{1/d} \tag{3.19A}$$

$$IOI_{SC} = (B \cdot d \cdot IOI_C)^{1/d} \tag{3.19B}$$

Since our goal is to determine $d\, lnIOI_{SC}/d\, lnIOI_C$, we take the natural log of both sides and differentiate it with respect to $lnIOI_C$, resulting in the desired expression (which will be substituted into equation 3.4 in section 3.1.3.1):

$$d(lnIOIsc)/\, d(lnIOIc) = 1/d \tag{3.20}$$

Fig. 3.11a shows a plot of the equation 3.19B in a log-log scale. The curves illustrate how the growth of operating ideas in the domain is influence by the values of interaction parameter *d*. It is clear that higher values of *d* negatively influence the slope of the curves, which represent the relative rate of IOI assimilation by the domains. It is also evident that the slope of the curve reduces in a non-linear fashion - fast as the value of d increases from 1 to a higher value, but later on it slows down. This is also clear from the plot of equation 3.20, the final relation (Fig. 3.11b).



(a) (b)

3.11: Growth of IOI_{SC} (successfully assimilated operating ideas in domains) using equation 3.19B: (a) influence d (interaction) on growth of IOI_{SC}, assuming B = 1 (b) how time derivative of logarithm of IOI_{SC} varies as a function of d.

The graphs in Fig. 3.11 suggest that interaction differences among domains can give rise to variation in improvement rates, and further they show how few interactions (d) are required to slow the assimilation of ideas by the domains. This variation is further expanded by scaling parameters associated with domains, which we discuss next.

3.1.3.6 Performance models - scaling of design variables

Our research question is concerned with intensive technological performance of domain artifacts. The intensive technological performance represents an innate performance characteristic of an artifact. We operationalize the notion of intensive performance by dividing desirable artifact outputs with resource constraints (e.g., mass, volume, time, cost). An intensive performance metric for batteries is energy density, kwh/m^3. We now consider three examples of relationships between intensive performance and design variables, and then utilize a more general relationship to account for the scaling effect of intensive performance.

3.1.3.6.1 Selected examples

We first consider blast furnaces used in the manufacturing of steel as representative of reaction vessels of various kinds. Widely used performance attributes for a blast furnace are capacity and cost, where cost can be considered the resource constraint. So, an intensive performance metric can be defined as capacity (output per hour or day typically) per unit cost. The capacity of a reaction vessel is determined by its volume, while its cost is primarily proportional to surface area (Lipsey et al. 2005). The following dimensional analysis shows that following these simplistic assumptions, intensive performance of a reaction vessel is linearly proportional to size, *s*.

$$Q_{RV} = \text{capacity/cost of reaction vessel} \propto s^3/s^2 = s^1 \qquad (3.21)$$

Gold (1974) has empirically shown that the cost of a blast furnace goes up by 60 percent when the capacity is doubled. Intensive performance Q_{RV} using this empirical finding goes up by 1.25 (=2/1.6) when volume (s^3) doubles. The doubling of volume corresponds to *s* scaling up by 1.26 ($=2^{.333}$), thus closely agreeing with the simply derived relationship 3.21.

A second example we consider is specific power output from internal combustion (and other heat) engines. Power output (kW) is proportional to volume occupied by the combustion chamber minus the heat loss from the engine, which in turn is proportional to the engine's surface area. The power and specific power can, then, be calculated as:

$$\text{power} = a\, s^3 - b\, s^2\,;\ b/a < 1 \qquad (3.22)$$

$$Q_{IC} = \text{specific power} \propto \text{power/volume of engine} = (a\, s^3 - b\, s^2)/s^3 = a - b/s \qquad (3.23)$$

Similar to reaction vessels, specific power output of IC engines increases with size so both are "larger is better" artifacts". For small values of $(b/a\ s)$ it is approximately linear with *s*. For larger values of *s*, it is less than linear in *s*.

As a final example, we consider information technologies, whose performance improvement ranks amongst the highest. Several modern information technologies depend upon integrated circuit (IC) chips. Electronic computers have been improving performance by reducing the feature sizes of transistors in IC chips for microprocessors. The number of computations per second per unit volume, an intensive measure of performance, depends upon frequency and number of transistors in a unit volume. Frequency is inversely proportional to the linear dimension of a feature, *s*, and the number of transistors per unit area is inversely proportional to area of the feature. Thus,

Computation per sec per cc $\alpha\ 1/s \cdot 1/s^2 = s^{-3}$ (3.24)

The dimensional analysis indicates that computations per second increases rapidly for a decrease in a linear dimension of a feature. This is due to the cubic (or higher)[24] dependence of computations per second on feature size. The negative sign captures the fact that the design variable needs to be reduced in order to increase performance, that is, smaller is better for this artifact.

3.1.2.6.2 Generalization

The three examples we have presented illustrate the notion that intensive performance improve by different degrees depending how the design variables are scaled (with A=+1 for reaction vessel, A=+1 for engine for small sizes, and A=-3 for computation). In the first two cases, a 10 percent increase in a design variable will improve performance by 10 percent or less. However, in the case of computations, for the same 10 percent change in design variable (feature size), the performance would improve by over 33 percent. This dependence is modeled as a power-law:

$Q = s^A$ (3.25) $\ln Q = A \cdot \ln s$ (3.26)

$d \ln Q / d \ln s = A$ (3.27)

[24] If the vertical dimension also decreases over time as the feature size decreases, a higher power, perhaps approaching 4, would apply.

Where, A is the scaling factor, s is the design variable in a domain J. Equation 3.27 shows that relative change in domain performance with respect to relative change in design variable depends upon the scaling parameter of the design variable. This is consistent with the pattern seen in the results of the examples in section 3.1.3.6.1.

3.1.3.7 Bringing all elements together

We now bring the results for rate of IOIs growth and influence of interaction and scaling together. For the reader's convenience, we reproduce equation 3.5 here, and substitute the results for the three factors:

$$\frac{d\ lnQ_J}{dt} = \frac{d\ lnQ_J}{d\ lns} \cdot (\pm 1) \cdot \frac{d\ lnIOI_{SC}}{d\ lnIOI_C} \cdot \frac{d\ lnIOI_C}{dt} \qquad (3.3)$$

Substituting the results from equations 3.27, 3.20, and 3.15B for the first, third and fourth terms on the right hand side, we get:

$$K_J = \frac{\mathrm{d} \ln Q_J}{dt} = (\mp 1)\ A_J\ \frac{1}{d_J}\ K_I \qquad (3.28)$$

Equation 3.28 represents the overall model of the annual rate of improvement for domain J. According to this equation, K_J, the annual rate of improvement of domain J depends upon K_I, the exponential rate at which the IOI_C pool increases in size. K_I is then modulated by domain specific parameters, d_J (interaction) inversely and A_J (scaling) proportionally to result in a domain specific rate of improvement K_J. The minus sign is converted into positive one by negative sign of A_J (for those cases where smaller is better). One observation to note is that A_J and d_J are constants for a given domain, thus resulting in a time invariant rate (or a simple exponential) for a domain.

This model identifies d_J and A_J as potential variables than can test this model. We present results from an empirical test for the first one in the next section.

3.2 Empirical study of domain interactions using patents

The theoretical model presented in section 3.1 suggests that the interaction parameter, which is characteristic of a domain, is one of the key factors in influencing the rates of performance improvement. This section presents results from an attempt to empirically test this theoretical finding.

3.2.1 Methodologies

3.2.1.1 Different approaches to study interactions: DSM and patents

Two approaches exist for studying interactions in artifacts. One method that is well recognized is the design structure matrix (DSM) (Eppinger and Browning 2012), which when applied to products captures interactions between components in any artifact. The empirical method essentially utilizes interviews with a broad variety of engineers who participate in development of an artifact and are associated with effort on various components or systems that make up the artifact. Such interviews can capture geometrical, energy, material and information interactions and the DSM can be defined at different levels of abstraction of the product and the method has been well developed for some time now.

If one can obtain reliable DSM data across a wide range of domains, this would be an effective way to study interactions. However, it is very expensive to develop a DSM for complex product such as a jet engines, aircrafts, and MRI machines. Perhaps for this reason, the number of DSM publicly available in papers and at websites is meager. Leading DSM researchers such as Prof. Steven Eppinger at Massachusetts of Technology recommend using the website ww.dsmweb.org as a potential source for DSM. After a significant amount of time spent searching and browsing through the available DSM for products, only few (~10) complete DSM were found, and most were for artifacts for which we did not have performance data. One DSM for jet engines by Pratt and Whitney, which could be associated with internal combustion engines for which performance data was available was found in a book by Eppinger and Browning (2012). No others were found and at least 10 would be needed for systems that have performance data in order to test the theory. Due to the scarcity of available data and prohibitive cost of developing them, this approach, to study interactions was dropped.

Another approach is to use documents - design manuals and engineering books - related to a specific domain, which could be analyzed using text mining techniques. Since not enough texts describing interactions related to specific domain could be found, this was not a promising approach either.

On the other hand, patents retrieved using the COM technique (Benson and Magee 2013, 2015a) for each specific domain for which performance data is available offered a promising avenue for study of interactions. As described earlier in the literature, patents as a data source are promising because they are generalizable, objective, qualitative and quantitative. They provide a wealth of text that describes state-of-art prior to the invention, and problems that were solved. Second, the data is publicly available for many generations of technologies, and easily accessible from USPTO or other websites such as Google.com. Unlike in DSM of products in which interactions have already been identified, interactions are not inherently defined in patents as patents are written for the protection of intellectual property, and patent law does not require them to be identified for patentability. Thus, it was necessary to develop a method for identifying interactions as a first step before any analysis could be done.

3.2.1.2 Overview of steps for text mining and analysis of patents

The patent analysis using a text mining approach was conducted in two phases. In the pilot study using patents from 5 domains - battery, wind power, solar PV, capacitors and computer tomography scanning (CT scan), feasibility for extracting data on domains interactions from patent text was explored, and basic procedures developed. After the keyword approach was shown to be feasible, an extended study using patents from 28 domains was implemented.

Both the pilot and full study consist of three broad steps shown in Fig. 3.12. In the first step, domain patents are identified, electronically retrieved from the web, and cleaned to prepare for analysis. In second step, interactions are retrieved from the domains using textual analysis, and are then analyzed in the third step. In the subsequent sections, these three steps are described in the context of a pilot study undertaken for the exploration of key-word based text-mining approach for studying interactions using patent text.

Fig. 3.12 Steps for analysis of domain interactions using patents

3.2.1.3 Preparation of text from domain patents

The outcome of this step was the relevant text from 100 most-cited patents for each of the domains being studied. The preparation followed the following procedure to retrieve the text for analysis:

- Identified 100 most-cited patents[25] for the domains using COM method (Benson and Magee 2013, 2015a) and eliminated any irrelevant patents by reading.
- Identified reliable source for patent text: Google patent database (html files).
- Selected useful patent sections for study of interactions.
- Retrieved patent sections using computer scripts and manually.

[25] The most cited 150 patents were obtained so that 100 could be retained after eliminating non-relevant patens.

- Eliminated extraneous text such as stop words from the patent text using Python scripts.

The first step in getting this text required identifying patents that belonged to each domain. The patents for 28 domains were identified as part of the doctoral work of Christopher Benson (2014) to study rates of performance improvement using patent-metadata. The current author was a participant in that research in reading downloaded patents from PatSnap, a commercial patent database, to test whether they belonged to the domain in question. To reduce noise due to non-relevant patents, this study was limited to 100 most-cited domain specific patents identified using COM technique; but these 100 patents were obtained after reading and eliminating non-relevant patents in this set. PatSnap was also used to identify the most-cited patents for the 28 domains. For the pilot study, only a sub-set of 5 domains, each with 100 patents, were studied

In the second step, a reliable source for retrieving patent text was identified. Although PatSnap allowed patent metadata including abstracts to be downloaded, it did not provide electronic access to the rest of the text in the patents that were intended to be used for text mining. Fortunately, Google patents provided an access to the text in patents as html files.

As part of the third step, two researchers, including the current author and an Intern working with the author for several months, read a set of 60 patents from 5 domains to identify sections describing technical issues that reflect interactions. Three patents from each decade starting from the 1970's till the present were selected to make a total of 12 patents in each domain. (See the literature review section 2.4.2 for description of the structure of patents.) It was observed that background or prior art sections, as expected, described problems with the state-of-art artifacts. It was found that many patents while summarizing the current invention also discussed problems that were not previously discussed in background or prior art section. In both of these sections, descriptions of problems, which could be interpreted as interactions, were observed. The detailed description and claims sections focused on describing the current invention and novelties they wanted to claim as assignee's intellectual property, and rarely included descriptions of interactions. Based on this reading, the decision was made to include text from the *title,* *abstract, background, and summary* sections, and not include the detailed description and claims sections.

Unlike in PatSnap, it was not possible to download patents in bulk, and required doing either manually or writing a web-scraping tool to automate the process. For the pilot study, the relevant sections were downloaded manually. (For the extended study a web-scraping tool was developed and used for downloading close to 2400 patents. The remaining 400 patents had to be downloaded manually.)

In the final step of preparing the patents for text mining, the stop words were removed from the patent text using Python scripts. Stop words are a set of commonly used words, such as *the, a, it,* and *in*. Although they are critical in natural language, they do not add any value to the data. Removing them makes it possible to focus on the important words, and reduces computation. The completion of this step prepared the text from 500 patents for text-mining.

3.2.1.4 Exploration of keyword-based text mining technique for extracting data on domain interactions

In preliminary work to develop a method for extracting data on domain interactions, three text mining approaches were explored using the100 most-cited patents for 5 domains. The first method was latent semantic analysis (LSA) and the second method was LDA (Latent Dirichlet analysis). Literature review section 2.4.5.3 on content analysis provide a description of these techniques. No promising signals regarding interactions were visible in the results provided from both of these techniques.[26] The third approach was keyword analysis which did yield useful results so it will now be described in more detail. First, an analysis of interactions was developed to guide the keyword search.

Types of interactions: Based on the work of Whitney (1996, 2004) and Suh (2001), the interactions in artifacts can be classified into four types:

[26] Results from these explorations are in the appendix for reference.

- Between functional requirements: These interactions are consequences of the dependencies between multiple functions and design parameters as discussed by Suh (2001). For example, increasing size of a mechanical component can increase the increase its stiffness, a desirable quality. But, increasing size results in increase of mass, which can affect dynamics of the artifact adversely. When one function is improved, such interactions can lead other coupled functions to be adversely affected.

- Between component and component: A good example of this type of interactions is the necessity to match impedance between sub-systems in order to transfer power efficiently (Whitney 1996, 2004).

- Between component behavior and system behavior.

- Parasitic/side effects: These represent undesirable effects exhibited by the components and sub-systems, while they fulfill their main functions. Some examples of these are corrosion in battery electrodes, and heat dissipation in computers.

Identification of keywords capturing interactions: A challenging aspect of the keyword approach is that it requires the researchers to identify words that represent interactions before the keywords can be searched in the patent text. In this study, keywords were identified by studying the 60 patents using the insight about the nature of interactions as guidelines.

In a preliminary study, two researchers, including the current author, re-read the same set of 60 patents described in section 3.2.1.3. This time they noted all instances of text representing interactions in each patent and compared the results from the two readers. The text which both researchers agreed on as representing interactions (any type of interaction described above) were retained for further study. From each description of interaction in the text, a keyword was identified that most closely captured the essence of the text describing the interactions. All the keywords were tallied in each domain. A total of 30 keywords were deemed to potentially represent interactions. However, most had low counts, and some were too specific to a domain, making the distribution across domains a large noise source.

Two criteria were used to cull the keywords: count of occurrence and general usage of the keywords across the domains. High occurrence was necessary to get a statistically strong signal capable of showing variation across the domains. For example, the words 'problem' and 'prevent' were common keywords to describe technical issues. Since the goal of the study is to conduct a comparative study, it was also necessary to ensure that keywords were not domain specific, instead were generally used. For this reason, the word 'corrosion' was not considered a good keyword, since it would be too specific to particular domains, and may see no usage in some domains. Instead the word 'prevent' or 'undesirable' would be a better choice, since it captures the notion of bad side effect that needs to be mitigated, but without considering the nature of the side effect.

The list was reduced to 8 keywords, which had high count and could be generally used across all domains. They are listed in Table 3.2. It is evident that all words are general and not domain specific. Table 3.3 presents examples of patent text with the keywords highlighted. In each case the text can be interpreted as an example of a description of an interaction described above. The interaction described in the first and second examples can be interpreted as undesirable side effects, whereas the third example pertains to conflict of functional requirements.

Table 3.2 Short-listed 8 keywords representing interactions

• **Parasitic** • **Problem** • **Prevent** • **Undesirable**	• **Requirement** • **Fail** • **Disadvantage** • **Overcome**

Table 3.3 Examples of text from patents describing interactions

- *This is probably due to penetration of the liquid electrolyte into the aluminum oxide surface coating on the anode. Sometimes, however, such penetration is* ***undesirable****, as it can result in a change in the dielectric characteristics and hence in a distortion of the waveform in pulse applications.*

- *In such electrolytic capacitors there exists the risk that the liquid electrolyte will leak out. Accordingly, the capacitor must be hermetically sealed to* ***prevent*** *any leakage of the liquid electrolyte therefrom...*

- *... has the advantage of permitting accurate superposition of graphic representations of surgical objects on fluoroscopic images of a body part without the* ***requirement*** *for registration of the body part itself.*

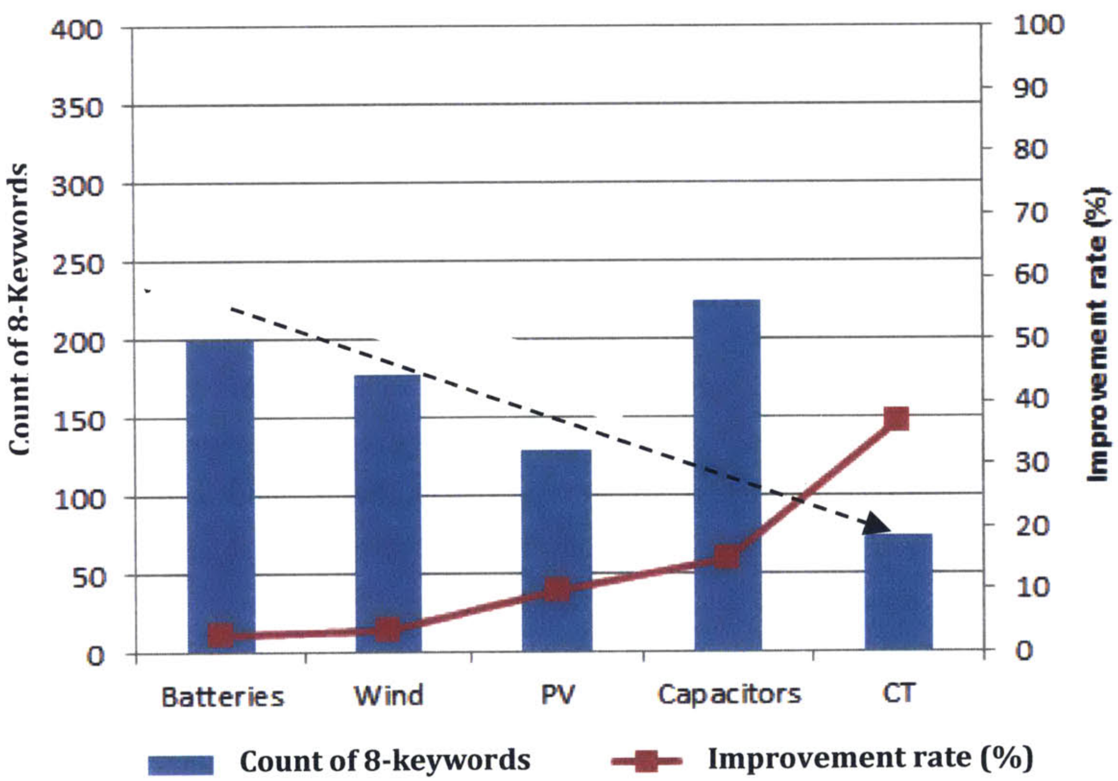


Fig. 3.13 Plot of count of 8-keywords representing interaction and improvement rates for 5 domains. The count of 8-KW trends downwards across the domains which are ordered with increasing performance rates.

These keywords were then searched in 86 patents in each of the 5 domains. The total count of keywords for the 5 domains are presented in Fig. 3.13. The total count of keywords (left Y-axis) are used for estimating the component interactions in the domain artifacts. The domains are ordered with rising improvement rates along the horizontal axis to see potential trends. The performance improvement rates for each domain are also plotted for reference. A general downward trend in count of keywords is clear, although the count of keywords for capacitor deviates significantly. Further, the correlation analysis provided that the correlation coefficient was 0.73, but with a p-value of 0.16. The general downward trend visually observable and good correlation-coefficient were both promising. However, p-value greater than 0.05 cautioned that this could be easily due to random effects, and further analysis was necessary.

The pilot study successfully demonstrated that patent text could be used for study of interactions, identified keywords potentially capturing domain interactions, and developed the steps necessary for conducting the study. Not surprisingly, the study was inconclusive, and suggested that it was essential to extend study to more domains.

3.2.1.5 Extended study of interactions with 28 domains

The extended study included 28 domain with 100 most-cited patents and followed the basic steps developed in the pilot study. Since this study required retrieval of text from 2800 patents, web-scraping tools had to be specifically developed for automated downloading of selected patents sections. Out of the 2800 patents, about 2400 hundred were successfully downloaded using this tool, and the rest had to be downloaded manually.[27] Almost all of these manually downloaded patents either lacked proper titles describing the sections, or background and summary were merged with detailed descriptions. For these cases, the background information and summary had to be manually identified by reading the patents and extracted.

[27] Since 24 patents could not be downloaded, the number of patents in each domain studies ranged from 97 to 100.

Following the techniques developed in the pilot study, the Python code was written to eliminate stop words, and extraneous text. Similarly, scripts were written for detecting and counting the keywords and extracting the portion of the text containing these keywords. In addition to the keywords, this study also counted the number of words and characters used in the patents and domains in order to normalize the count of keywords.

The following section presents the results and the analysis for the extended study.

3.2.2 Results and analysis

This section presents statistics from text-mining of 2800 patents, and results from correlation analyses followed by results from robustness studies. The final sub-section summarizes the results.

3.2.2.1 Count of words across domains

We first present patent statistics based on text mining of patents. Fig. 3.14 shows the total count of words in the title, abstract, background, and summary of each of the 2800 patents studied. The X-axis represents the serial number of the patent we assigned, which are ordered as domains shown in Fig. 3.15. It can be observed that there is a wide variation between patents, with some patents being very wordy. The wordiest patent has over 15 thousand words. There are also a large number of patents with total count of words exceeding 3000 words. The ratio between the highest and the lowest counts is more than 100. Although this is the case with individual patents, when the domains are viewed collectively as a group, the variation tightens. Fig. 3.15 shows the total count of words per domain. The domain level word count ranges from roughly 95,000 to 191,000, a ratio of slightly over two, which is much tighter than a ratio of 100. The domain with the five highest word count in descending order are genome sequencing, 3D printing, optical memory, CT scan, wireless telecommunications. The domains with lowest count in ascending order are electric motor, electrical telecommunications, milling machine, optical telecom, and flywheel. Although the variation has shrunk, it may be large enough to skew or add significant noise to total count of keywords representing interactions, and thus pointing to the need to normalize the keyword count for analysis.

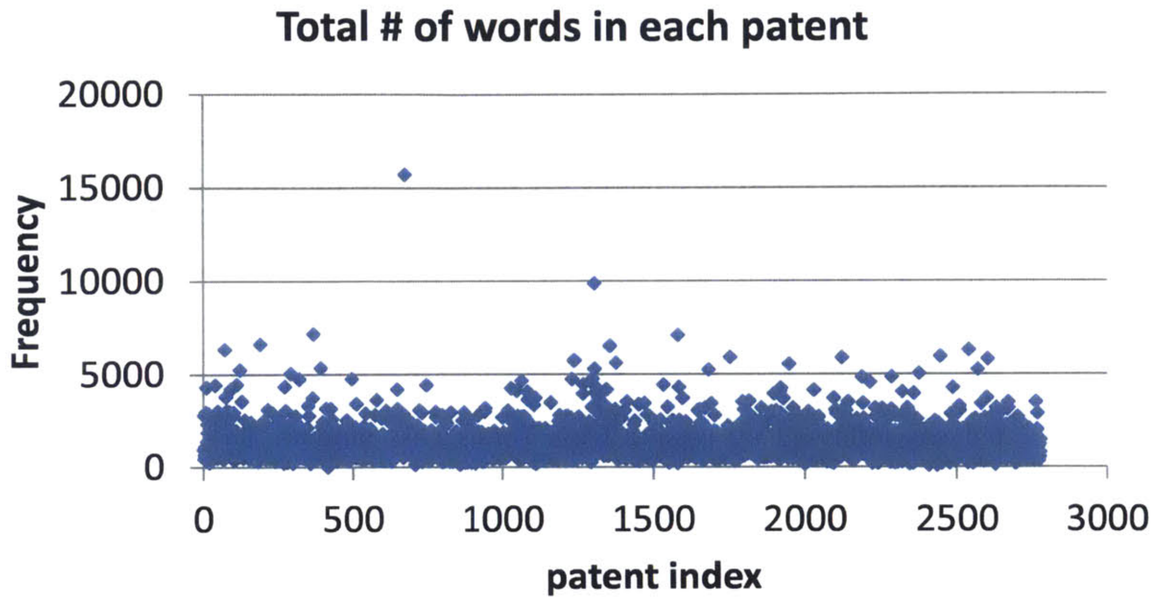


Fig. 3.14 Variation of count of words in 2800 patents

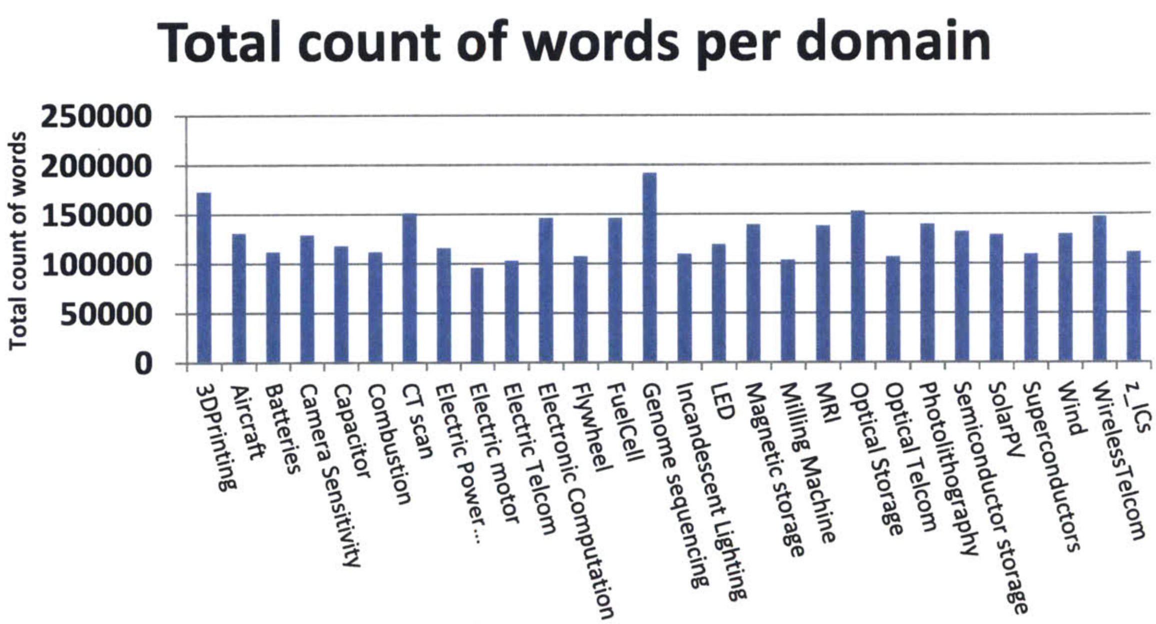


Fig. 3.15 Variation of count of words per domain

3.2.2.2 Normalized count of keywords

The study of 28 domains was begun with 8-keywords – *parasitic, problem, prevent, undesirable, requirement, fail, disadvantage, overcome* – which were identified in the pilot study. The normalized count of 8-keywords for 28 domains are presented in Fig. 3.16. Since the 8-keyword count for each domain is much smaller than the count of words, the normalized 8-keyword count has very low fractional values. To make it easier for the reader to comprehend, the normalized 8-keyword counts have been expressed for every 100,000 words. It can be observed that five domains that have the highest normalized 8-keyword count in descending order are Aircraft domain, Electric Power Transmission, Flywheel, Electric Telecommunication, and Milling Machine. The domains that have the lowest count in ascending order are Genome sequencing, CT scan, Superconductors, MRI, 3DPrinting. Annual rates of improvement for 28 domains are reproduced again for reader's convenience in Fig. 3.17.

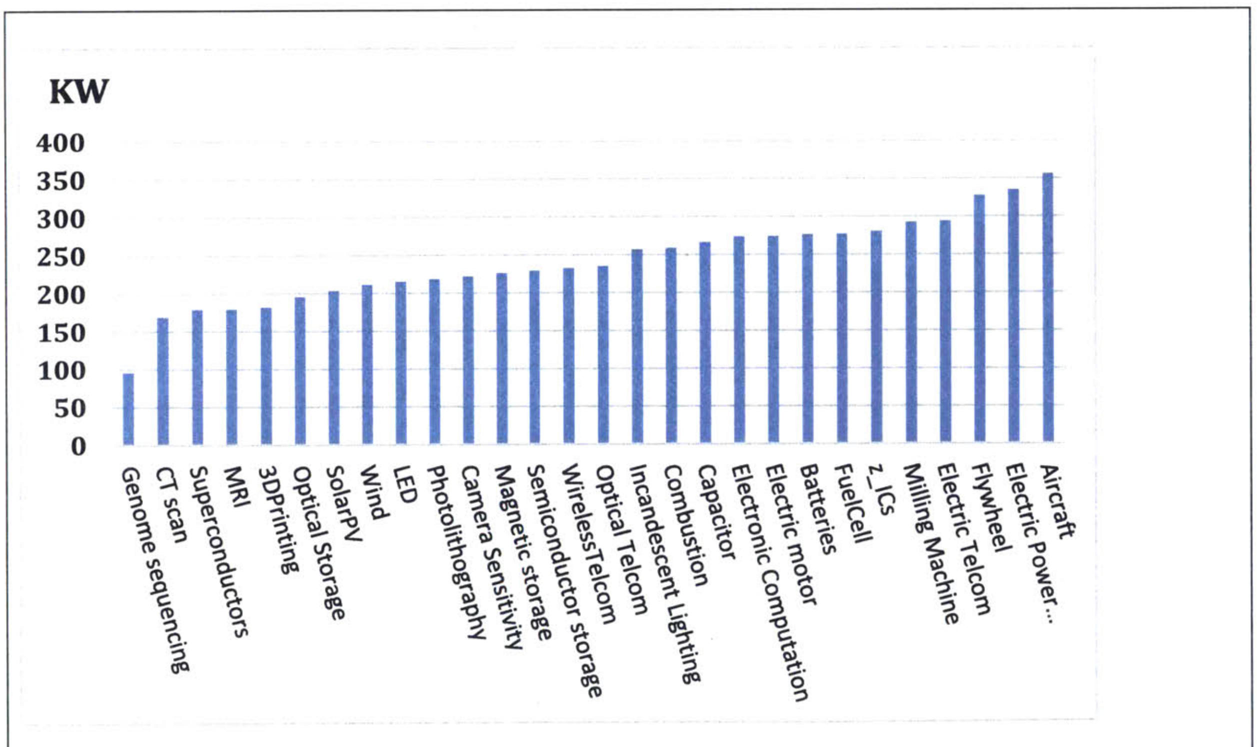


Fig. 3.16 Count of normalized 8-keywords per 100,000 words for 28 domains.

3.2.2.3 Correlation analysis of normalized keyword count and annual improvement rates

This correlation analysis treats keyword count as the independent variable and annual rate of improvement of domains as the dependent variable. Fig. 3.18 shows a scatter plot of the annual rates of improvement (Y-axis) and the normalized 8-keyword count (X-axis) for 28 domains to observe any form of correlation visually. We can see that data is quite noisy, with noisiness higher for lower counts of 8-keywords. The data point for genome sequencing appears as if it might be an outlier. Nonetheless, the downward trend is visible, implying that increase in 8-keyword count is correlated to decrease in annual rate of improvement. The Pearson's correlation coefficient calculated using EXCEL 2010 is -0.41 with a p-value of 0.016. The p-value indicates that there is only 1.6% probability that this correlation is due to randomness. The correlation coefficient has a medium value; this implies that keyword count, as an independent variable, alone is not able to explain the variation in annual rates of improvement.

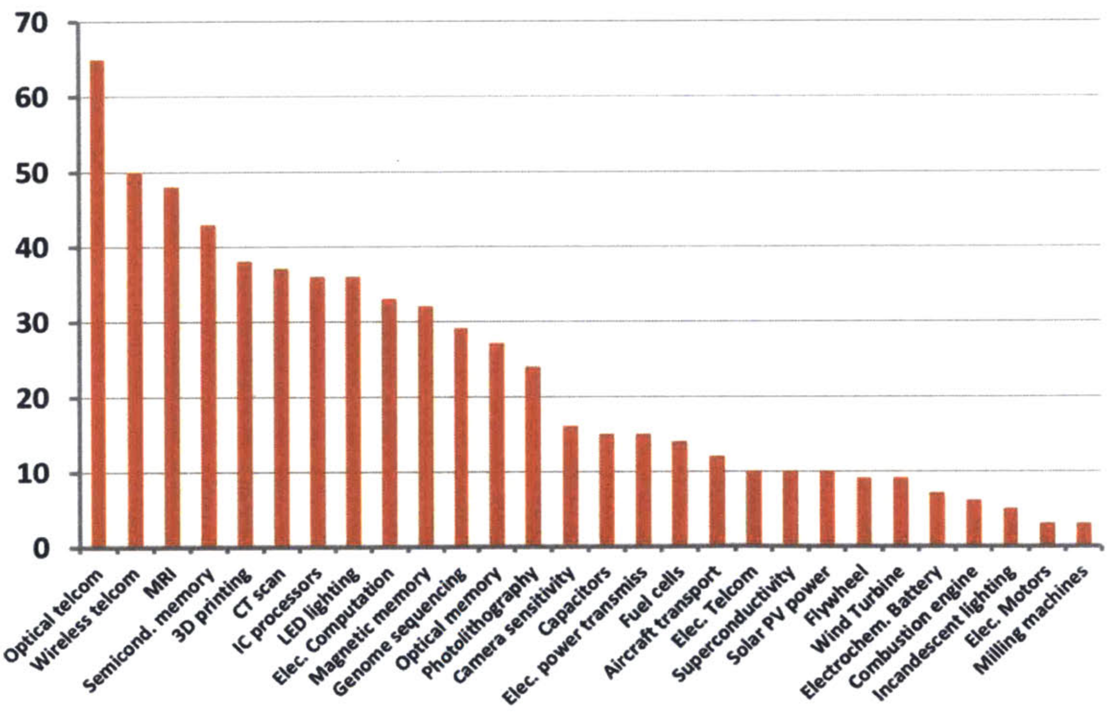


Fig. 3.17 Annual rate of performance improvement for 28 domains. Adapted from Magee et al. 2014.

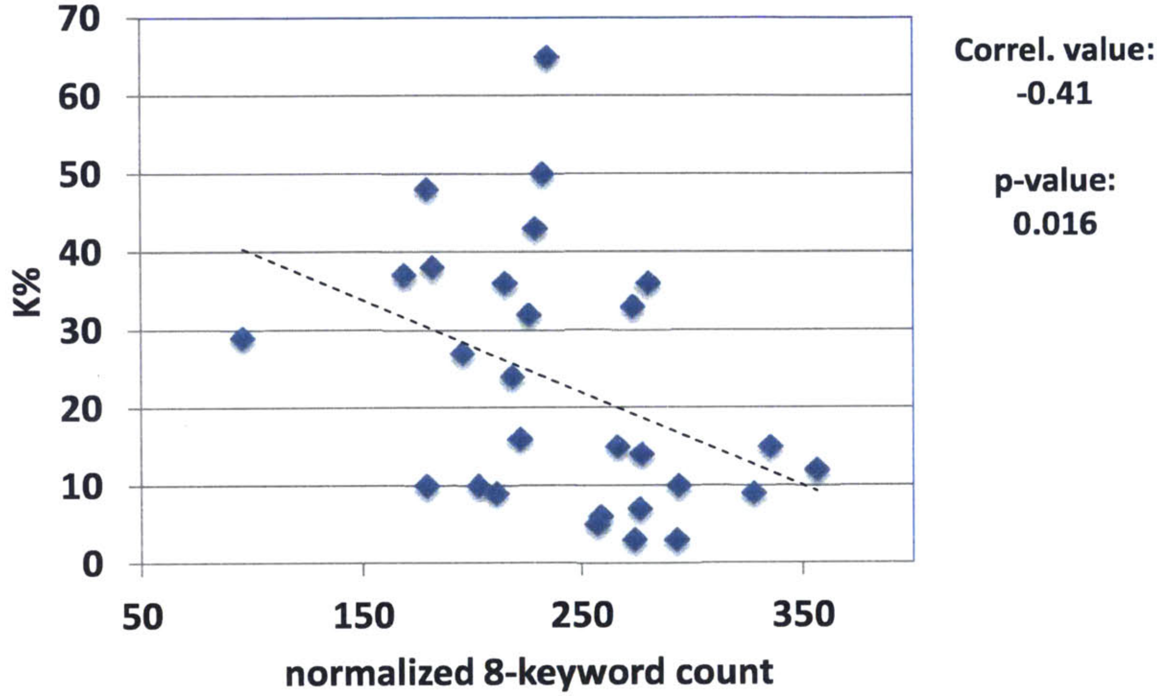


Fig. 3.18 Scatter plot of normalized 8-keyword count and annual improvement rates for 28 domains (using ~100 in each domain)

These results are based on 8-keywords selected through the pilot study using two criteria - relevancy and cross-domain usage.

As part of the pilot study using 5 domains (battery, capacitor, wind, solar power and CT scan), apart from correlation study, relevancy of the 8-keywords had been studied. Two readers separately examined the text from 12 patents from each domain containing these keywords and determined whether the meaning of a keyword as used in the text represented an interaction, and calculated the relevancy results. The relevancy value for a specific keyword for a domain was calculated as a ratio of the count of a keyword when it represented an interaction to total count of the same keyword (whether it represented an interaction or not). Table 3.4 presents relevancy results for the keywords in each domain. The top row lists the domains and the left-most column, the eight keywords. The last columns presents the average values of relevancy of a keyword across all domains. All 8 keywords have consistently high relevancy except for the keyword problem which has only 0.58. This is because it is common among engineers to use the word 'problem' to describe design opportunities, such as in a phrase 'design problem'. This convention is reflected in the patent text. Since such usage does not capture interactions, low relevancy is likely to add to the noise. For this reason, 'problem' was removed from the keyword list.

Table 3.4 Relevancy of 8-keywords obtained during pilot study

Percentages:	Batteries	Wind	PV	Capacitors	CT	Arithmetic mean
parasitic	0.99		0.99	0.94		0.97
problem	0.68	0.61	0.55	0.50	0.55	0.58
prevent	0.93	0.85	0.76	0.85	0.75	0.83
undesirable	0.875	0.95	0.99	0.99	0.875	0.94
requirement	0.85	0.69	0.79	0.81	0.63	0.75
fail	0.92	0.68	0.78	0.74	0.50	0.72
disadvantage	0.93	0.80	0.79	0.80	0.71	0.81
overcome	0.99	0.96	0.99	0.95	0.99	0.98

The seven remaining keywords were examined against another criteria – cross-domain usage. Six out of seven words are used by all 28 domains. Although highly relevant with a value of 0.99 when it was used, the "Parasitic" keyword, however, was not widely used by many domains. In fact, in 12 domains it was not even used once, and only 4 domains – Camera Sensitivity, Capacitor, Electric Power Transmission, Fuel Cell, IC chips - used it often. Fig. 3.19 shows the distribution of the "parasitic" keyword across 2800 patents. Note the areas that have only zero values, indicated by arrows. To provide perspective, the distribution of the keyword "prevent" is presented in Fig. 3.20. It is clear the keyword "prevent" is widely used across domains, apparent from the lack of regions with zero values.

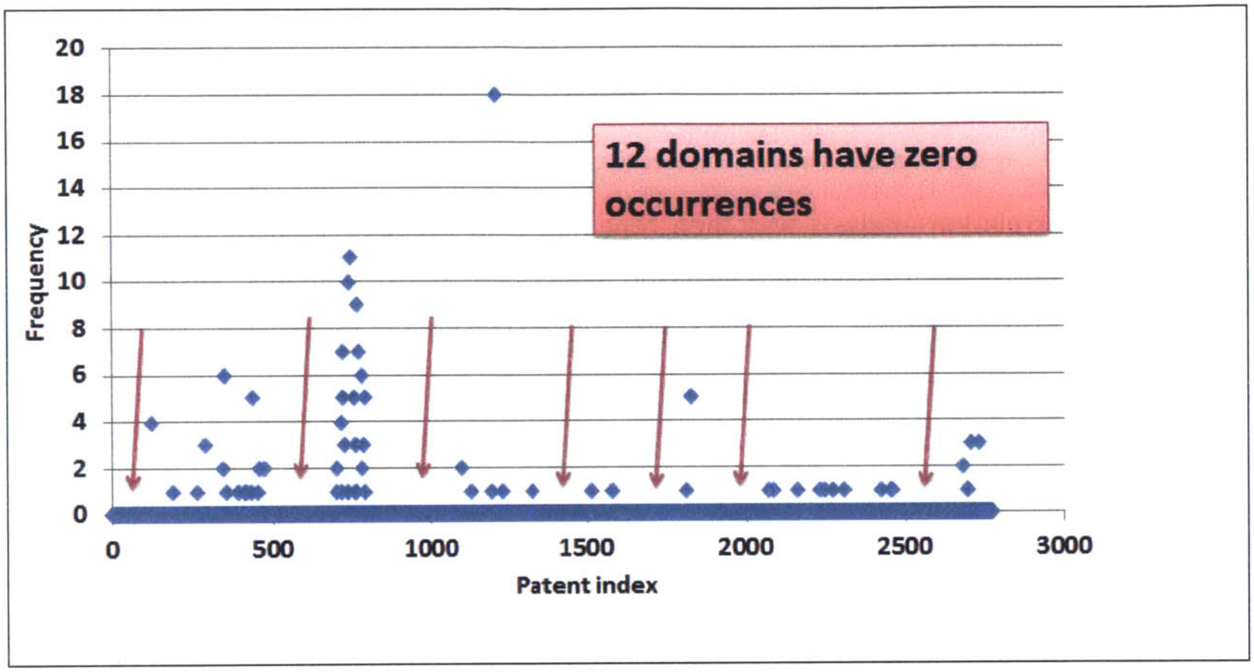


Fig. 3.19 Distribution of "parasitic" keyword across the patents. Note areas which have mostly zero values pointed by the arrows.

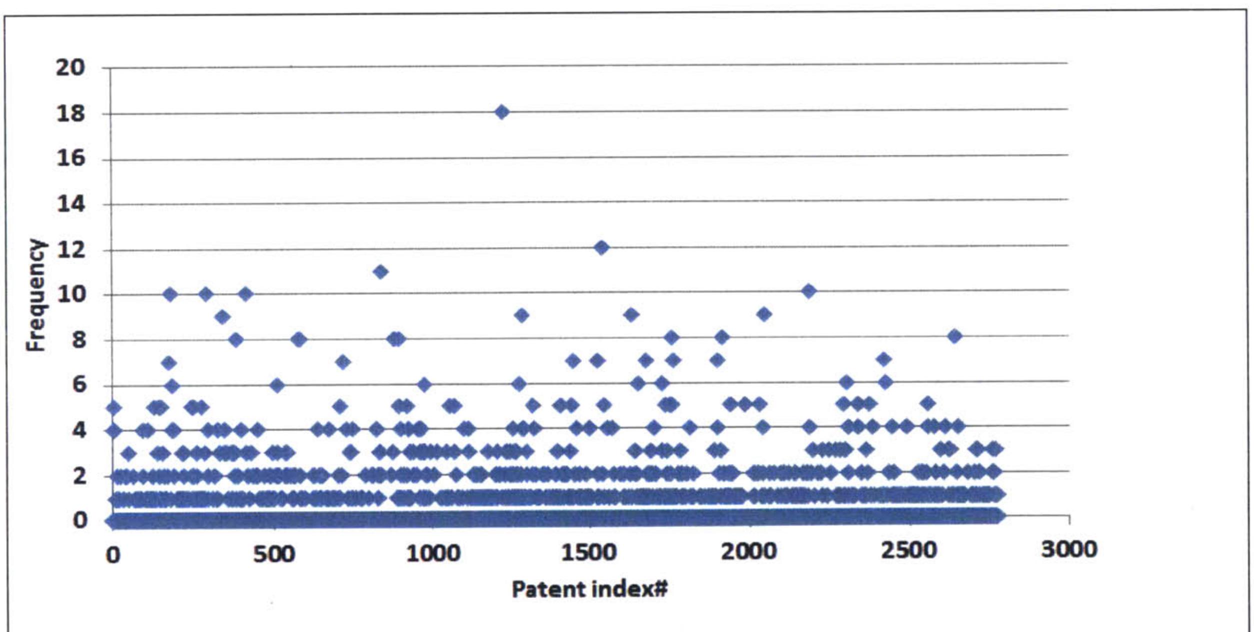


Fig 3.20 Distribution of "prevent" keyword across the patents. Note the high cross-domain usage of this word

The two keywords - problem and parasitic - do not satisfy the two criteria and would only add to the noise, hence it was decided to eliminate them from the key word group.

The correlation analysis was then repeated with using only six keywords, which have both high relevancy and high cross-domain usage across domains. Results from a correlation analysis using six-keyword count for 28 domains are shown Fig. 3.21. Visually, it can be observed that the data points are less scattered and the downward trend is more visible, showing a negative correlation. As expected Pearson's Correlation coefficient (calculated using EXCEL2010) has improved from -0.41 to -0.554. Similarly, the p-values

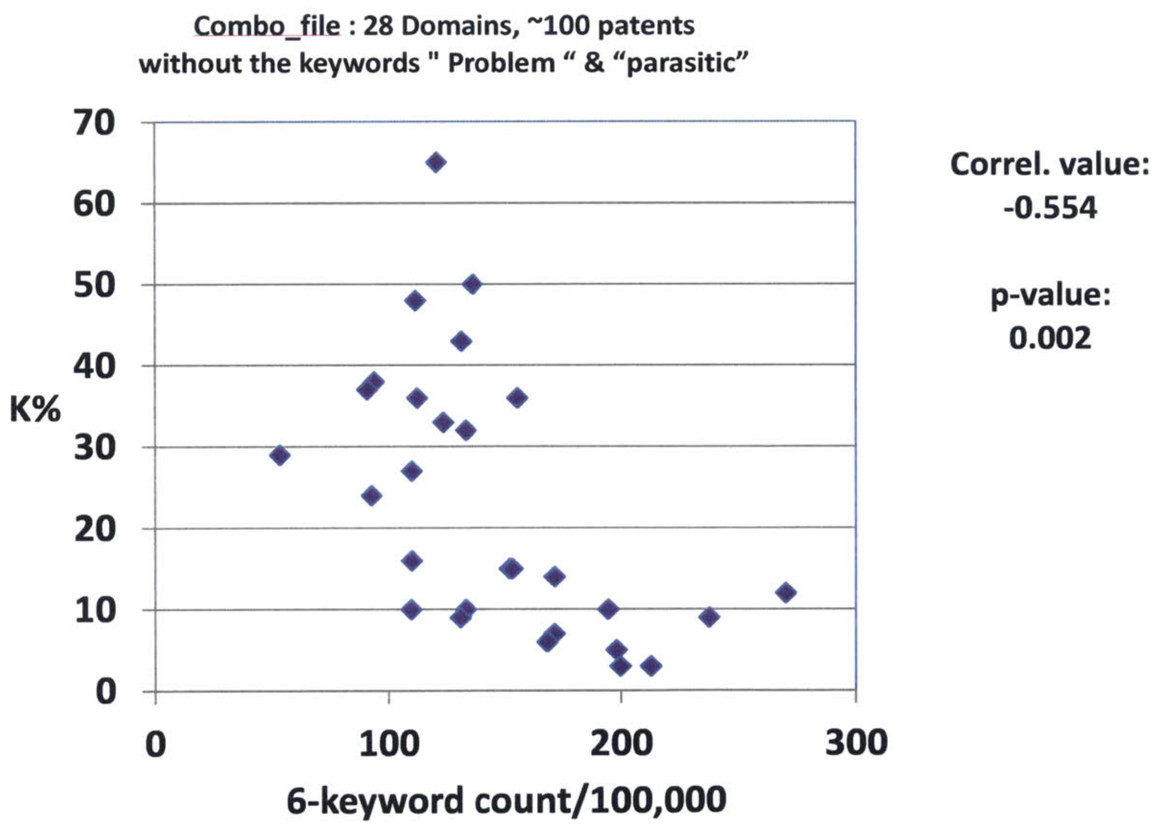


Fig. 3.21: Correlation analysis of normalized 6-keyword count and annual improvement rates

has further decreased to only 0.002, indicating that there is even less chance that this correlation is due to random effects.

3.2.2.4 Correlation analysis of reciprocal of normalized count of keyword and annual improvement rates

The correlation analysis presented in the previous section assumed a simple linear relationship between annual improvement rates and their 6-keyword counts. The model that was developed in section 3.1, however, states that annual rates of improvement should be inversely proportional to the interaction parameter *d*. The equation has been reproduced and the relationship plotted using a proportionality constant of 0.35 (See Fig. 3.22), where the interaction parameter *d* takes values 1 or larger.

$$K_J = \frac{d\, lnQ_J}{dt} \propto \frac{1}{d} \qquad (3.29)$$

Implication: *Domain with higher number of interactions improves at a slower pace in a non-linear fashion.*

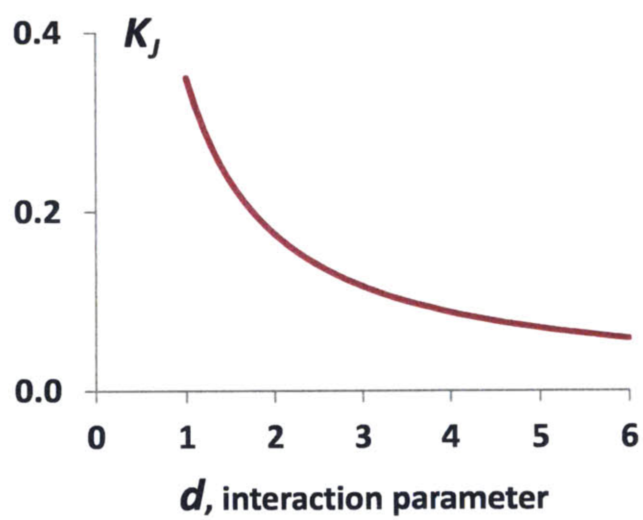


Fig. 3.22 Plot showing how d (interaction parameter) influences non-linearly.

The interaction parameter d as explained in section 3.1.3.5 represents an average number of out-links from components in a domain artifact. The keyword count provides a measure of interactions engineers encountered in generating inventions. Although both are different approaches to quantify interactions in a domain, the exact of nature of the relationship between these two measures of interactions is not known. The analysis is carried out by assuming a linear relationship between the two. With this assumption, the above relationship then becomes

$$K_J = \frac{d\, lnQ_J}{dt} \propto \frac{1}{d_J} \propto \frac{1}{6keyword\ count_J} \quad (3.30)$$

This relationship was then tested empirically using the 6-keyword results. The results from a correlation analysis between reciprocal of 6-keyword count and K_J for 28 domains are shown in Fig. 3.23. Although there is significant noise in the data especially due to data point for genome sequencing, it can be observed visually that there is a clear upward trend showing that higher annual rates of improvement correlate with higher values of the reciprocal of 6-keyword count. Correlation value calculated using EXCEL2010 is +0.43 with a p-value of 0.034. Although p-value is less than what was observed with previously presented correlations, it is still less than 0.05, a threshold value typically employed by many researchers.

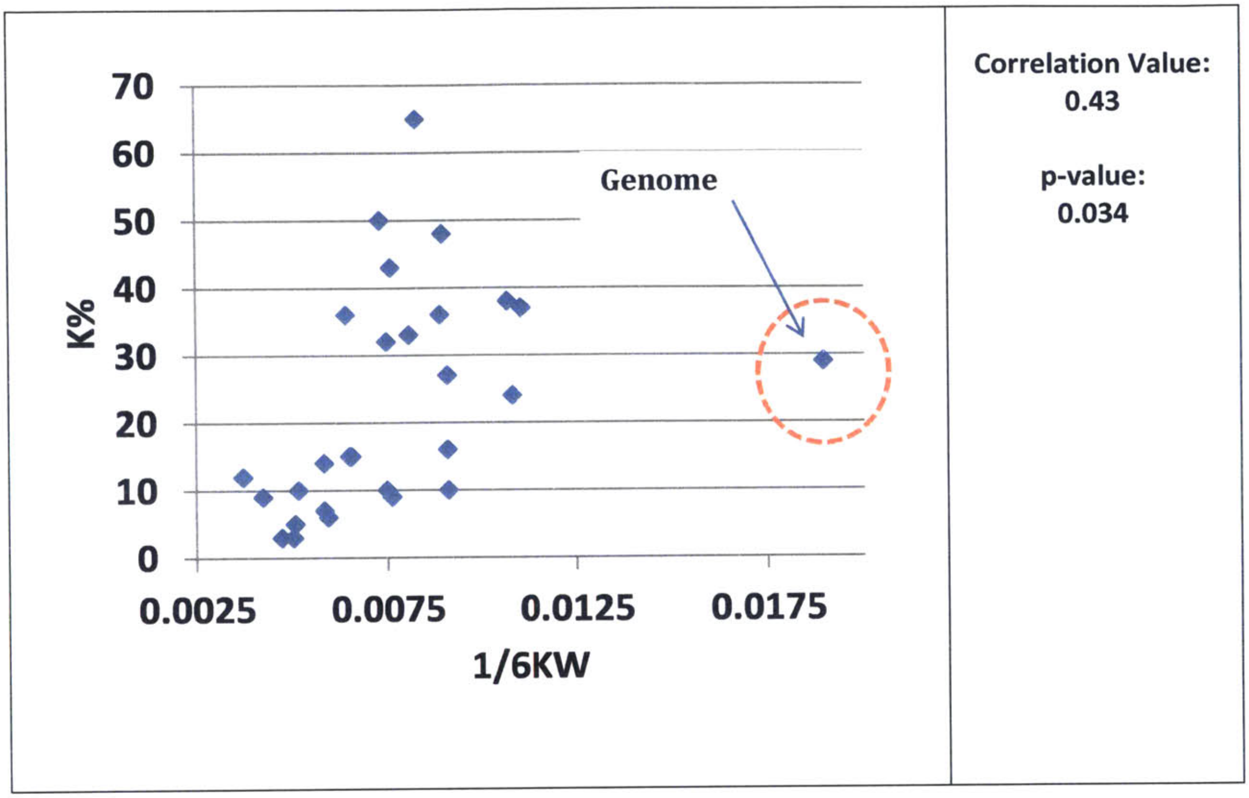
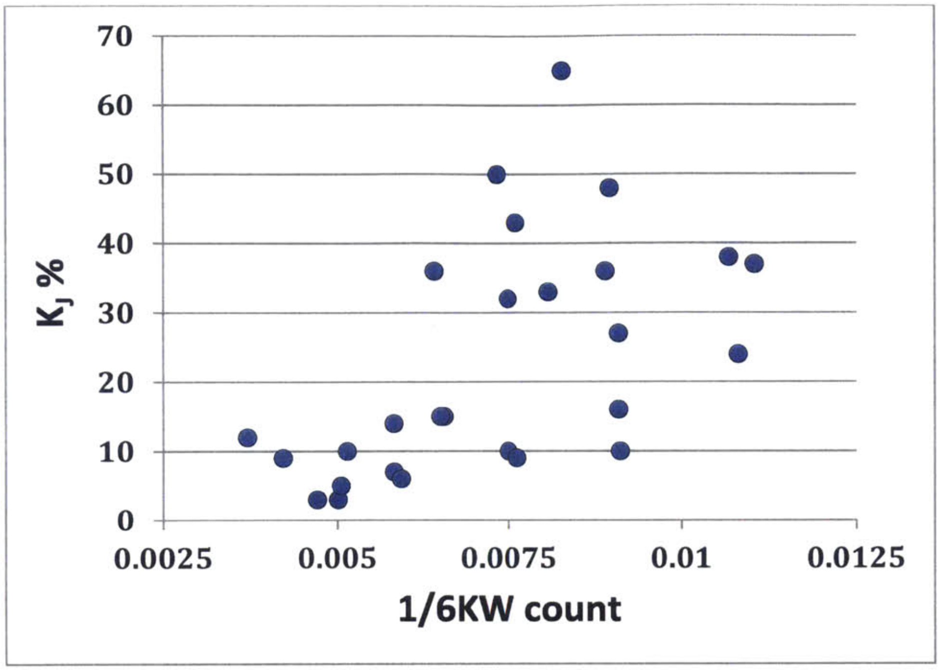


Fig. 3.23 Scatter plot of K and reciprocal of normalized count of 6 keyword for 28 domains

The genome sequencing data point appears to be an outlier, being very far away from the rest of the data points. It was noted earlier that Genome Sequencing data point might be outlier when results for 8-keyword correlations were presented. This reciprocal of 6-keyword has heightened and clearly shows its distance from most of the data. Recall from section 3.2.2.1 that genome sequencing had the highest number of total word count, thus making the normalized keyword count small. Genome sequencing patents tend to have many chemical formulae included in the background and summary sections. This may have contributed by inflating the word count for genome sequencing, and thus distorting the value of normalized 6-keyword count. If this is so, it makes sense to categorize it as an experimental error and exclude genome sequencing from the correlation study. Fig. 3.24 shows the scatter plot with the Genome sequencing removed. And, correlations coefficient without Genome Sequencing jumps to +0.56 with a p-value of 0.002.



Correlation Value: +0.56

p-value: 0.002

Fig. 3.24 Scatter plot of K and reciprocal of normalized count of 6 keyword for 27 domains (without Genome Sequencing)

The analysis showed that count of 6-keywords were negatively correlated with medium correlation coefficient, but a low p value indicating that the finding (even with genome sequencing) is reliable. To further examine the reliability of this finding, a robustness study was conducted.

3.2.2.4 Robustness test results

The robustness study was conducted to examine the stability of the correlation coefficient and the p-value. The study was conducted by creating 20 groups of 14 domains, where each group was generated by randomly selecting a combination of 14 domains from the 27 domains. For each group, the correlation coefficient between improvement rates and 1/6KW values were calculated.

The results of those 14 groups are presented in Fig. 3.25 with the index number of each group plotted along X-axis, and Pearson's correlation coefficient along the Y axis. The statistics are summarized in Table 3.5. It is clear from the figure that correlation values are quite closely scattered and there are no outliers. The correlation values range from +0.81 to +0.41, with a mean of +0.59 demonstrating that the correlation value is relatively stable. This analysis also demonstrates that the correlation value (+0.56) obtained in the initial study with 27 domains was not due to random effects associated with particular domains.

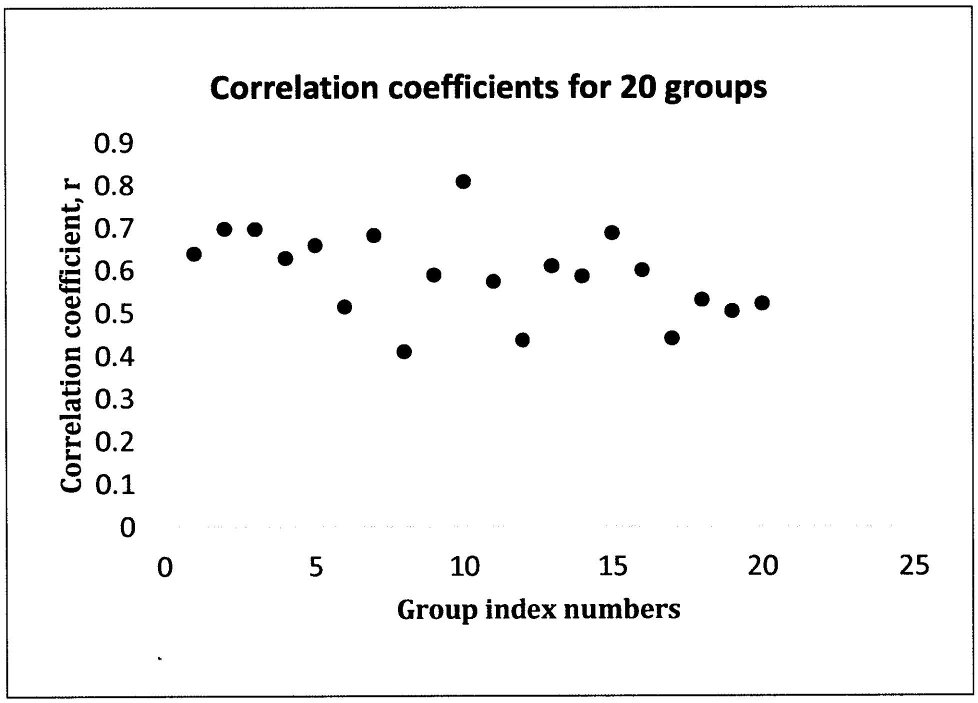


Fig. 3.25 Scatter plot of correlation coefficients for the 20 groups

Table 3.5 Summary of correlation results from robustness study

# of Keywords used in robustness test	Range of Correlation coefficients (Max, min)	Average Correlation coefficient (r) for 14 groups	p-value for average r
6	+0.81, +0.41	+0.59	0.001

3.2.3 Summary of empirical test results

The empirical study developed a keyword-based approach for extracting interaction information from patent sets for specific domains. It identified 6 keywords that captured the idea of domain interactions, and were non-domain specific, and relevant, thus making them general. According to the method developed in this thesis, the normalized total count of these 6-keywords provides a measure of domain interactions. Using this method, the study extracted interaction data for 28 domains. Equipped with this data, correlational analyses with normalized 6-keyword count and performance was conducted to test the following hypothesis:

> **Hypothesis:** *Keyword count representing interactions in a set of patents in technological domains is negatively correlated to rates of performance improvement in the domains.*

This hypothesis was tested using two approaches. First, the correlational analysis tested it assuming a *linear relationship* between normalized count of 6-keywords (independent) and performance improvement rates (dependent). The test showed that these variables were correlated with coefficient of -0.55 with a p-value of 0.002. The p-value 0.002 shows that probability of this correlation occurring due to random chance is only 0.2 % (a low value). Most researchers reject null hypothesis if the p-value is equal or lower than 0.05; this study has adopted this threshold p-value. Accordingly, the p-value of 0.002 is clearly much lower than 0.05 and hence the null hypothesis is rejected.

The second correlational study tests the mathematical relationship suggested by the model. This model suggests that domains with higher count of keywords (reciprocal of which will be a lower value) will improve at a slower pace than the domains with lower count of keywords; however, they will so in a non-linear fashion. The correlation study was made using a reciprocal of normalized count of keywords, transforming non-linear relationship into a linear one. For the 27 domains (with the outlier domain removed from analysis), the results showed that performance improvement rates were positively correlated with the coefficient of +0.56 with a p-value of 0.002. With this p-value, the null hypothesis can be easily rejected.

It has to be noted the both of these approaches (linear and non-linear) have established that high count of normalized keywords for domains are negatively correlated with performance improvement rates of respective domains. With similar values of correlation coefficients, the correlation studies, however, have been unable to discern the form of the relationship - linear or non-linear. It will be argued in the discussion section 4.3 that the linear relationship leads to inconsistent predictions, and should be discarded and the other one kept.

3.3 Permanent Magnetic materials: A Case Study

3.3.1 Introduction

Permanent magnets have pervaded a large number of modern artifacts including toys, power tools, medical devices, computers, MRI machines, hybrid vehicles and wind turbines. With significant improvement in performance, engineers are now able to design more compact and lighter devices, such as motors, thus allowing the technology to continue to diffuse into more applications. Reduction in size of motors has been so dramatic that a single car nowadays has over 30 motors installed in it (see Fig. 3.26). Their ubiquity across diverse applications (see Fig. 3.27) across many technological domains makes it an attractive choice to examine how the domain encompassing permanent magnetic materials has improved over time and how its improvement compares with other technologies.

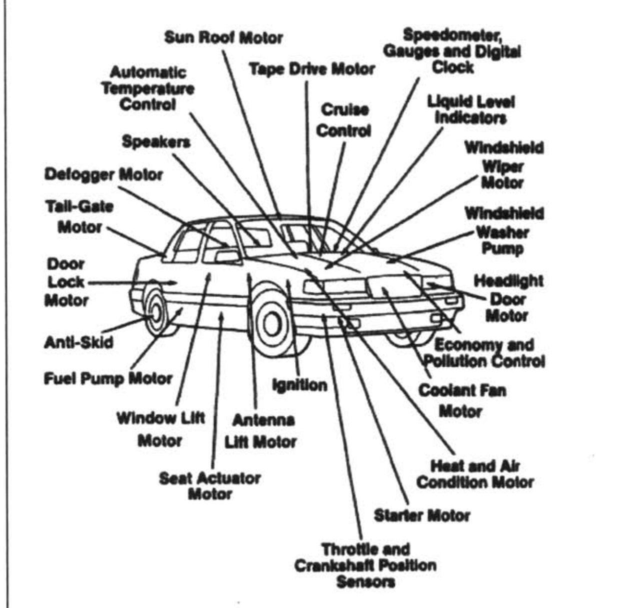


Fig. 3.26 Pervasive applications of permanent magnets in car. From Livingstone 1990.

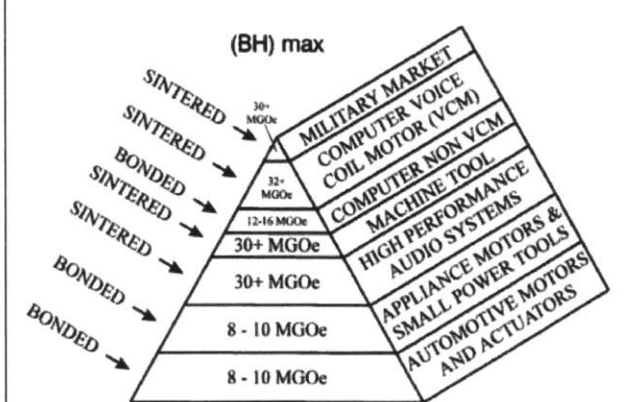


Fig. 3.27 Typical application of permanent magnets depending on the energy density (BHmax). From Rashidi 1989.

Improved permanent magnets clearly must result from discovery or creation of new materials and thus it differs somewhat from the other domains studied thus far. Some scholars (van Wyk et. al. 1991) have described this particular domain as experiencing a series of S-curves, which provides another conceptual reason to study carefully. We also add this domain to our rates database to test findings in C. L. Benson's thesis and in this thesis that were based upon the 28 domains. Key questions include: 1) whether the rate predicted by the Benson and Magee regression equation based upon patent meta-characteristics is consistent with the actual rate of performance improvement found in this case study and 2) whether the interaction word metric found in this case study is consistent with the results found in this thesis. Thus, the case study will consist of:

- Performance improvement with time
- Patent search and the set of relevant patents
- Tests of prior work
    - Benson/Magee regression
    - Interaction parameter and fit with this thesis

3.3.2 Performance improvement with time

3.3.2.1 History of the technological domain

Permanent magnetic material has been known to humans since the time of ancient Greek civilization. Modern magnetic materials, however, have been around for only slightly more than two centuries (Livingstone 1990). At the turn of 19^{th} century, magnets made from carbon steels, which were mechanically harder and had high coercivity were still in use. This correlation between mechanical hardness and coercivity led to the term "hard permanent magnetic material". Alnico as a permanent magnetic material was introduced in the 1930s. This had significantly higher energy product. Ferrite, also introduced during the same decade, had lower performance, but was much cheaper, for this reason it is still used extensively. Around the mid-1960s, Sm-Co based permanent magnets were introduced, which quickly surpassed the performance of Alnicos. Sm-Co magnet gave way to Nd-Fe-B (rare earth magnetic materials) based permanent magnets in early 1980s. Sm-Co based magnetic materials are now more often used for high temperature applications.

3.3.2.2 Function, physics and performance metric

The primary function of a permanent magnet in energy storage and transformation artifacts is to provide magnetic flux. They are also used for other purposes such as sensing and information storage. Several properties of permanent magnets are considered desirable for their applications. Coercivity, remanence and maximum energy product, however, are the most technologically important properties (Livingstone 1990). Fig. 3.28 illustrates these magnetic properties using a stylized magnetization curve, also known as a B-H curve. The X-axis is the magnetizing field H and Y-axis the magnetized strength B, a response of the magnetic material being measured. Remanence is a measure of the residual magnetization B after the magnetizing field H has been reduced to zero, and reflects its ability to retain magnetic strength. In contrast, coercivity is a measure of the reversed magnetizing field H required to reduce the magnetization in the permanent magnetic material to null. This property measures the strength of a permanent magnet to resist from being demagnetized from opposing magnetic fields. The energy product, BHmax, is a measure of the maximum energy density of a magnetic material, and is defined as a rectangle with the maximum area (shown as a shaded rectangle in Fig. 3.28) which can be inscribed inside the second quadrant of a magnetization hysteresis curve. This property, as the name suggests, reflects how much energy a magnetic material with a given volume can store. Other desirable properties are Curie temperature, mechanical strength and hardness, and corrosion resistance. These, however, are considered secondary (van Wyk 1991).

BHmax, represented by the area of the shaded rectangle, is indirectly influenced by both coercivity and remanence, and further it is intensive by definition. Consequently, BHmax alone is enough to capture performance. Additionally, it is also the metric of choice among engineers for rating permanent magnets. The SI unit of energy density for magnets is Joules per cubic meter (Jm^{-3}). Another unit popular among the scientific community is the MegaGauss-Oersted (MGOe), where Gauss is used for measuring B, and Oersted for H.

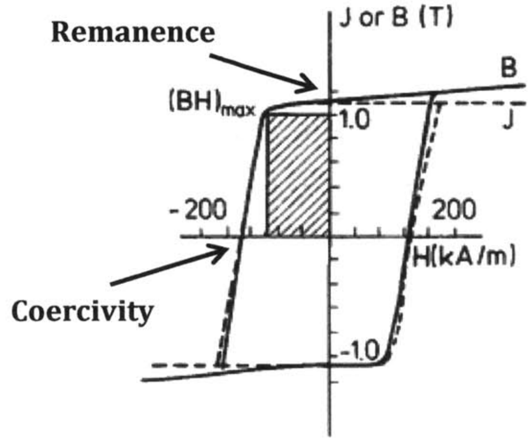


Fig. 3.28 Magnetization curve of permanent magnets.
Adapted from Livingstone 1990.

3.3.2.3 Performance results

The data for energy product was compiled from articles published in peer-reviewed journals, and conference proceedings. Although some data can be found in commercial companies manufacturing or distributing magnets, the articles from peer-reviewed journals was preferred for reliability.

Improvement in energy product of permanent magnetic material is plotted in Fig. 3.29 a, b. The first graph shows improvement against a linear scale with time on the X-axis, and performance on the Y-axis. Fig. 3.29 b exhibits the same data on a semi-log graph. It has to be noted that the plot shows only non-dominated values of performance; each non-dominated data point represents the best performance that has been achieved up to that point in time. Alternatively, they can be seen as record-setters.

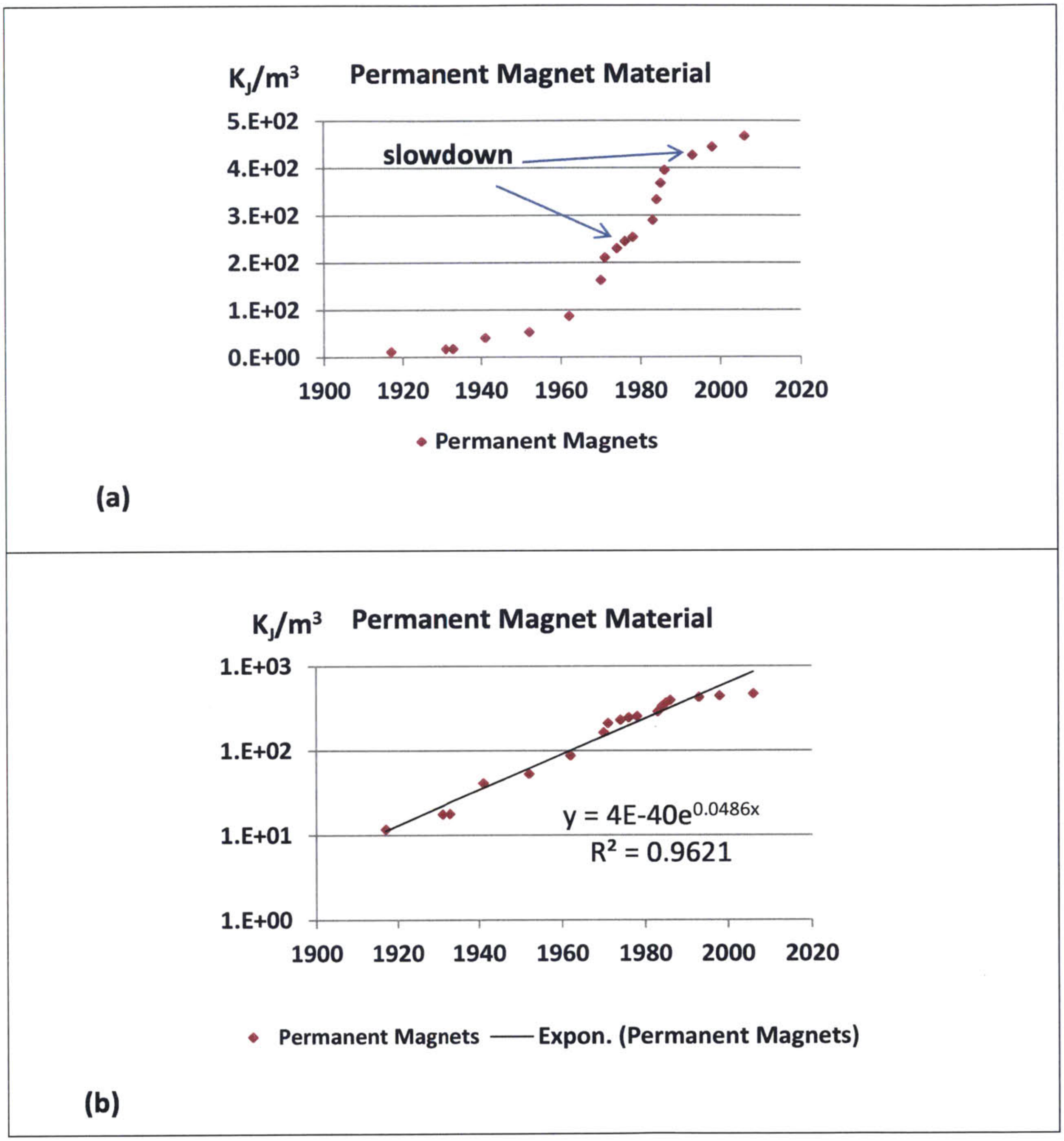


Fig. 3.29: Improvement in performance of permanent magnet materials in (a) linear (b) logarithmic scales on Y-axis.

It is evident from the first plot that there is substantial deviation in the latter part of the data (see Fig 3.29b), and there are apparent slowdowns. The domain appears to have experienced reduced improvements during the 1970s and 2000s, apparently encountering some barriers. The first slowdown was overcome by neodymium-based magnetic materials replacing samarium-based magnetic materials, while the second one still holds as no successor to neodymium-based magnetic materials is (yet) apparent. In spite of the deviations and slowdowns, the exponential fit of the data is still very good with an R^2 of 0.96 (Fig. 3.29 b). Based on this exponential fit, the annual rate of improvement in the energy product of permanent magnet material is calculated to be 4.86 percent from 1917 to 2006. Comparison of this improvement rate with technological domains demonstrates that permanent magnet materials falls among the more slowly improving domains, such as milling machines, incandescent lighting, and combustion engines. See Fig. 3.30.

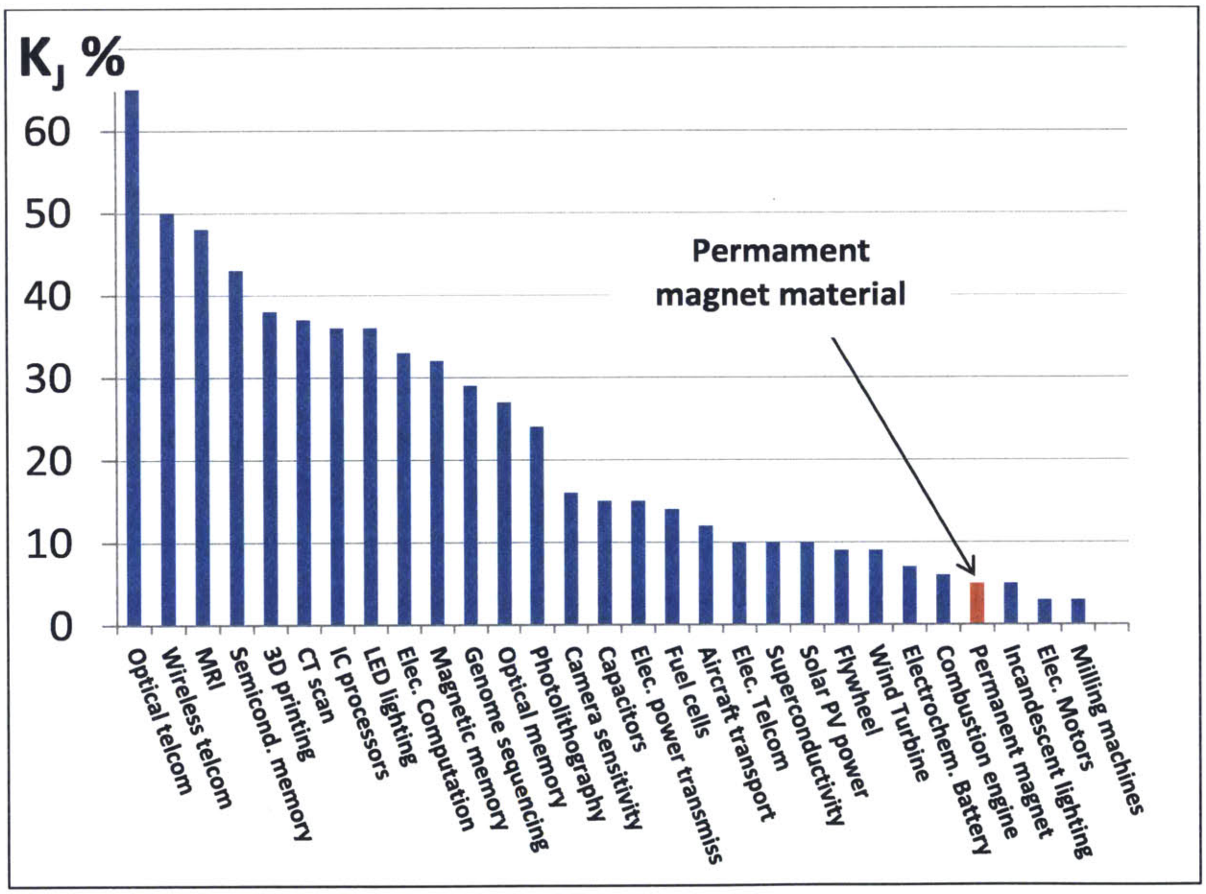


Fig. 3.30: Comparison of annual improvement rate (K_J %) of permanent magnet with those of other domains. Data adapted from Magee et al. 2014.

3.3.3 Patent search and set of relevant patents

The domain patents were identified using the classification overlap method (COM) (Benson and Magee 2013, 2015), which was discussed in the literature review. Using this technique, one sub-class from international patent classification, *HO1F* (basic electric material) and two UPC classes 420 (alloys and metallic compositions) and 335/302 (electricity: magnetically operated switches, magnets, and electromagnets) were identified to include patents related to permanent magnetic materials. The following query in PATSNAP was used to search for the final set of patents:

(CCL:(420 OR 335/302)) AND ICL:(H01F) AND (APD:[1976-7-1 TO 2013-7-1])

Intersection of HO1F with 420 produced 709 patents, while the intersection of HO1F with 335/302 produced 622 patents for period starting in July 1976 to July 2013. However, the query when executed as a single command produces 1321 patents, showing that only 10 patents were in both of the individual overlaps.

To examine how relevant the patents were to this domain, 300 patents were read by two readers independently to reduce subjectivity. Among these, the first 100 included most-cited patents, and the other 200 were randomly selected from the remaining patents after removing the 100 most-cited patents. Only those patents deemed relevant to the domain by both readers were considered. Based on the reading, the patents were 74% relevant, which is better than an acceptable rate. It has to be noted that patents based on new applications of magnetic materials were not considered as relevant as they do not reflect improvements in the magnetic material itself. If one were to include those patents as well then the relevancy would have been above 95%. For studying interactions, "clean" 100 most-cited patents were utilized. The term "clean" refers to the idea that patents that were not deemed relevant to the domain were removed, keeping only those patents considered relevant.

3.3.4 Testing prior findings with the permanent magnet case results

3.3.4.1 Performance improvement rate estimated from patent metadata

Christopher Benson, a former colleague in our research laboratory, had studied the same 28 domains using the patent's metadata. (In contrast, the interaction study keywords uses the text from the patents.) He had found that the average number of citation received by the patents in first three years after publication and their average publication year were strong indicators of that domain's annual rate of improvement. To examine how the permanent magnetic material domain fares from this perspective, the two patent characteristics were determined using 1321 patents and are shown below in table 3.6.

Table 3.6: Patent meta-characteristics of permanent magnetic materials domain

Meta-characteristics	Value
Average citations received by a patent in first 3 years	1.75
Average publication year	1999.59

The regression model based on average citations in first 3-years and average publication year of domain patents is presented below from (Benson and Magee, 2015b):

$$\boldsymbol{K_J = -31.1968 + 0.1406 * cite3 + 0.0155 * average\_pub\_year} \qquad (3.31)$$

Where *cite3* and *average_pub_year* are respectively average number of citations received by, and average publication year of, each domain patent. Using the values presented in table, the predicted annual rate of improvement is 4.3 %, which is very close to the observed value of 4.86 %.

--3.3.4.2 Influence of interactions on performance improvement rate

In section 3.2, the domain interactions were explored empirically to assess whether interactions are involved in creating the variation in rates of improvement as suggested by the model. The 6-keywords *prevent, undesirable, fail, requirement, overcome,* and *disadvantage* were finalized for examining domain interaction. The normalized 6-keyword count for each of the 28 domains using 100 patents were determined using text mining techniques. Following a similar method, the 100 most-cited patents from permanent magnet domain were also studied as part of this case study to determine interactions in this domain. The results for the 28 domains and for the permanent magnetic material are reproduced in Fig. 3.31 as a scatter plot of 6-keyword count and annual rates of improvement. It is clear that interactions reflected as 6-keyword count and rate of annual improvement is within the scatter band for the other 28 domains. However, the rate is lower than expected based upon the regression equation.

The linear regression model relating 6-keyword count and annual rates of improvement is as follows:

$$\boldsymbol{K_J = -0.1897 \cdot count_{keyword} + 50.575} \qquad (3.32)$$

Where K_J is the annual rate of improvement of domain J and $count_{keyword}$ is the normalized keyword count. The normalized count of 6-keyword for permanent magnetic material was 140. Using this equation, the predicted value of K for permanent magnet is 24 percent. This can be visually approximated using the trend line in Fig. 3.31. This predicted value is far from the observed value of 5 percent (annual rate of improvement). It can be seen that there is a lot of scatter associated with domains that have low 6-keyword count, making the predictability less reliable.

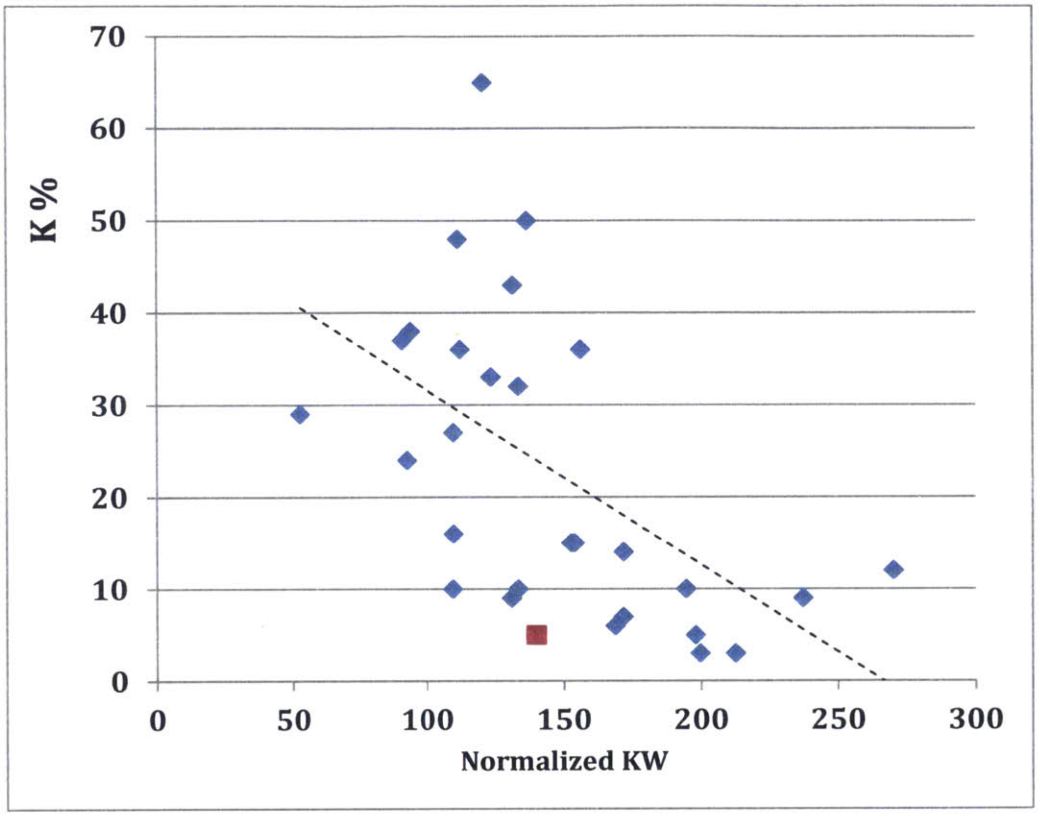


Fig. 3.31 Scatter plot of normalized count of 6-keywords and performance improvement rates for 28 domains (blue diamonds), and permanent magnetic material (red square)

In conclusion, the permanent magnetic material domain provides an example of a domain that has experienced slowdowns. In spite of the slowdowns, when viewed on a long time scale, it is still growing exponentially, albeit at a slower pace. It was evident that this domain is amongst those that are growing at the slowest pace. The 6-keyword count for this domain follows the general trend shown by other 28 domains, thus providing support to those results. Although the correlation between 6-keyword count and annual rates provides good support to the notion of interaction leading to variation in rates, it is necessary to develop it further to improve its predictive capability. The predicted result using patent characteristics (Benson and Magee 2015b) is close to empirically observed rate in this case study, and thus strengthens support for its predictive capability. However, more case studies need to be conducted to develop further support since this is a single case study.

Chapter 4: Discussion

This chapter presents discussion of three sets of results (from modeling, empirical test, and performance trends for permanent magnet materials) in the context of the technical change literature. The final section assesses the model with respect to the salient features of a theories in general and theories of technical change. We start with a discussion of results from the study of permanent magnetic materials.

4.1 Discussion of performance trends of permanent magnetic materials (PMM)

The review of the technical change literature in section 2.1 presented the performance trends for 28 technological domains. These results are the empirical foundation for the work in this thesis as the modeling and related empirical work on interactions is entirely aimed at understanding these results and moving towards a predictive theory. Thus, adding to this body of work, even if in a modest way, was undertaken as part of the thesis to experience more directly the context for the empirical foundations for the thesis. In this research effort, permanent magnetic materials (PMM), which has pervasive applications across diverse domains, was studied as an additional domain in order to study the nature of its improvement and to test out the findings in C. L. Benson's thesis (2014) and in this thesis.

The performance metrics for the 28 domains (Magee et al. 2014) followed exponential trends and their annual rates of improvement varied from 3 to 65%, whereas the performance of PMM was 4.9 %. Compared with the performance of other 28 domains, the performance of PMM with annual rate of only 4.9% falls among the domains which are slowest to improve. Only three domains – incandescent lighting, electric motors, and milling machines – have performance lower than this domain. Interestingly, two of them - milling machines, and electric motors – incorporate magnetic materials: milling machines utilize electric motors as a fundamentally important component, and electric motors similarly utilize magnetic materials.

Another interesting aspect of this domain is that it has indeed experienced slowdowns in performance, as noted by van Wyk (1991), during two periods – in the '70s and the '90s. The arrival of Neodymium magnets helped to break past the first slowdown in the early '80s. The second slowdown period associated with Neodymium that initiated in early '90s has yet to be broken. It is noteworthy that the domain studied here shows one of the clearest cases of "halting" behavior which our overall model does not try to predict (but the small IOI_0 simulations do show such behavior). Thus, it reinforces the fact that the empirical base is still contested by practitioners who are convinced that limits are the most important phenomenon.

Aside from studying the performance trends, the case study also tested two regression models utilizing the PMM's performance data in conjunction with domain patent data. Using the COM (classification overlap method) technique (Benson and Magee 2013, 2015a), a patent set of 1321 patents with 74% relevancy were retrieved, which provided two sets of patent data. Patent meta-characteristics from the first set were utilized to test the first regression model (Benson and Magee 2015b), which utilizes average citations in the first 3 years after the publication date and average age of the patents set to predict K_J, the annual rate of performance improvement for the domain. The average 3-year citations for this domain was 1.75 years and the average publication year was 1999.6, calculated using all the patents in the domain. With these data as the input, the regression model predicted 4.3% annual rate of improvement. This is quite close to the measured value of 4.8% showing it is one of the domains where the Benson/Magee regression equation fits closely (overall the regression has a R^2 of 0.64 so not all domains are expected to be this closely in agreement).

To understand the significance of this result, it has to be noted that Benson and Magee (2015b) had developed the regression model using the performance data and corresponding patent meta-characteristics for the 28-domains. The performance data and patent meta-characteristics for the permanent magnetic materials domain was developed as a separate case study, and was not included among the 28 domains. Although this is a first and singular case, the fact that this was done separately and yet the predicted and observed values are so close provides support for the soundness of the model. This also emphasizes the significance of the 3-year citation and average publication year as predictors of improvement rates. The average 3-year citation captures the idea of importance (how influential the patents in average have been), and immediacy (how well the current technical knowledge on average has been used in the domain) whereas average publication year captures the newness of patents in the domain (or recency of utilized information).

For testing the second regression model, the study used textual data, instead of meta-characteristics, from the 100 most-cited patents from the PMM patents[28]. The second regression model correlates the domain performance with a normalized count of 6-keywords representing interactions. Text mining and analysis of data showed the normalized count of keywords for PMM was 140. The plot of performance and the count of normalized keywords showed that the normalized count of keywords falls within the scatter band of other 28 domains, although it is towards the edge of the scatter, showing that the finding for PMM is consistent with data for 28 domains. With a normalized keyword count of 140, the regression model predicts the expected rate to be about 24%. This is significantly higher than the observed rate. However, this is not surprising since the correlation coefficient was -0.55 and there was a wide scatter in the low keyword count region. We discuss next the results from the modeling effort.

4.2 Discussion of model development

The primary goal of this thesis is to develop a mathematical model that utilizes mechanisms in the design/invention process to examine the nature of technological performance improvement trends. The exploration has utilized two sets of well-known mechanisms in the literature to build an analytical mathematical model. The first set of

[28] Since the relevancy is about 74%, the two researchers read patents to identify those not related to PMM. Only relevant 100 most-cited patents in PMM domain were used for getting the data for the second regression model.

mechanisms include combinatorial process based on analogical transfer, and mutual exchange between Understanding (largely science) and Operations (largely technology) regimes. The exploration has utilized simulation to gain insight into dynamics of the synergy that emerges from these two mechanisms. The second set of mechanisms includes two well-known fundamental features of artifacts - interactions (some refer to it as complexity) and scaling. The subsequent sub-sections examine: (1) the consistencies of the model with empirical results (and what is known about technical change) (2) assumptions made in the model and how they constrain the conclusions one can assert from the model (3) implications of the model.

4.2.1 Consistencies of the model with known findings in the literature

According to the model, the operational regime may be decomposed into idea and artifact realms. The exponential nature of performance improvement for all technological domains arises in the idea realm of the operational knowledge regime, where new inventive ideas are created using combinatorial analogical transfer of existing ideas, which, in turn, become the building blocks for future inventive ideas. The model demonstrates this incessant cumulative combinatorial aspect of knowledge in both the understanding and the operation regimes which manifests as exponential trends.[29] The combinatorial model is simple but it leads naturally to the exponential behavior with time that has only been obtained previously by Axtell et al. (2013) in a model that went beyond performance to diffusion over a set of agents. Such exponential behavior with time is consistent with one of the most widely noted behaviors of technical performance (Moore 1965, Koh and Magee 2006, 2008, Nagy et al. 2013, Magee et. a. 2014). The modeling work presented here provides some quantitative empirical support to the basic combinatorial concept of technological progress previously supported qualitatively (for example, Usher 1954).

[29] In technological domains, a combinatorial aspect has been observed at the artifact level, such as combination of a motor to a manual drill to obtain a power drill, but such combinations are limited in terms of what might be possible to combine. Instead, combination at the idea level through analogical transfer is far more expansive, depending upon the level of abstraction utilized in the ideas. Thus, operating ideas typically associated with some specific technological domains, which are considered distant, can also combine.

The Operation (technology) and the Understanding regimes (science) can improve independently in the model but not indefinitely. How long the Operation regime can improve depends in the model upon the size of the technological possibility space, which according to the model is dependent on the number of existing basic IOI (fundamental operation principles). The understanding regime can also experience stagnation, but this happens when the tools and instruments that scientists and researchers use for discovery and testing hypotheses are not adequate. The operational regime comes to its rescue by providing these tools and instruments (increased numbers of individual operating ideas), which greatly enhances the scientists' ability to discover and test, and thus further push the limits of understanding in the manner suggested by Price (1983), Gribbin(2002) and in the following quote from Toynbee (1962).

> *Physical Science and Industrialism may be conceived as a pair of dancers both of whom know their steps and have an ear for the rhythm of the music. If the partner who has been leading chooses to change parts and to follow instead there is perhaps no reason to expect that he will dance less correctly than before.*

In this sense, the operations regime and the understanding regime are like two independent neighbors who interact for mutual benefit. In the model, their frequency of exchange, however, influences their effective rate of growth. Our model is a specific realization that achieves this mutual interaction that has previously been widely noted in deep qualitative research.

The results in Table 3.1 (in chapter 3, section 1) are summarized as a surface plot in Fig. 4.1. K_I, the effective rate of growth of IOI_C was determined by the initial IOI_0, and the frequency of exchange (α $1/\ln R$). The former determined the envelope of technological possibility space. When IOI_0 are high, the effective rate of growth K_I is close to the theoretical combinatorial rate determined by Equation 3.10 {= $\ln(1+ P_{IOI}/2)$ }, irrespective of whether there was frequent exchange. However, when the IOI_0 are low, the limit is hit repeatedly, translating into halting and reduced effective rate of growth. The value of K_I in this case was determined by the frequency of enabling exchange from the understanding regime, with higher frequency (low R) leading to higher effective rate. With sufficiently high frequency, even with low initial IOI_0, the effective rate K_I eventually approaches the theoretical rate.

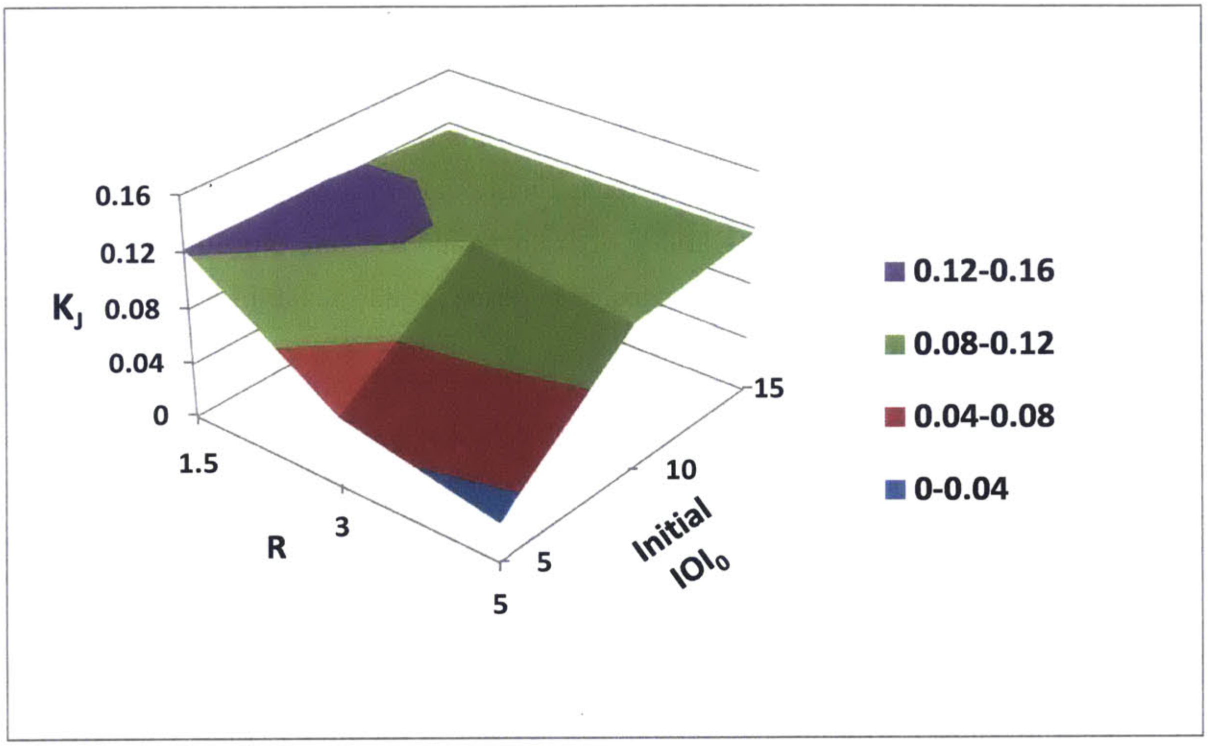


Fig. 4.1 Variation of K_I as a function of initial IOI_0 and R. Lower R refers to higher frequency of interaction with the understanding regime.

Detailed historical studies of technological change (Mokyr 2002) note centuries of slow, halting progress that eventually becomes much more rapid and sustained starting in the late 18th century in the UK. An interesting consistency of these observations with our model is seen since our model attributes the transition to sustained higher improvement rates to the combinatorial growth of individual ideas that are able to reinforce one another by the analogical transfer mechanism. That our model partially accomplishes this through the synergistic interaction of science and technology is also consistent with the detailed historical studies as interpreted by many observers (Schofield 1963, Musson 1972, Rosenberg and Birdzell 1986, Musson and Robinson 1989, Mokyr 2002, Lipsey et al. 2006).

The model is also consistent with the empirical findings of Benson and Magee (2015b). In particular, they found no correlation of rates in domains with effort in a domain (measured by number of patents or patenting rate) or with the amount of outside knowledge used by a domain (this is very large for all domains). They interpreted their findings by a "rising sea metaphor" that represents all inventions and scientific output being *equally* available to all domains but that fundamentals in the domains determine the rate of performance improvement. Overall effort in science and invention increase the rates in all domains but the differences among rates of improvement are due to differences in fundamental characteristics among the domains. The model in this paper identifies interactions and scaling as two such fundamentals and equation 3.28 is specific about the variation expected due to these two fundamental characteristics.

Thus, our model is consistent with much that is known in empirical literature; but to what extent does it achieve the ideal level of understanding mentioned in section 2 when discussing the related Benson and Magee research? It is - as desired - based upon what is known about the design/inventive process and does not rely upon characteristics only determined by observation of output in a domain; but does it make any reliable predictions based upon only "design knowledge"? We next consider this issue, along with the assumptions and limitations of the model.

4.2.2 Assumptions and limitations of the model

The model aspires to be predictive for technological performance. However, it is not fully reliable yet as there are assumptions in the model that have not been tested empirically and some of the mechanisms are conceptual and not testable. However, some of the findings do relate to design knowledge and are potentially possible to test with further research. We now consider the assumptions, their impact on the conclusions and what further research they suggest. Table 4.1 lists the assumptions that will now be discussed further.

A fundamental aspect of the overall model is that it differentiates between the idea/knowledge and artifact aspects of design and invention. Such decomposition is an essential step in arriving at our key result (equation 3.28 from equation 3.5). It is not clear that this assumption is testable so it must remain an unverified assumption or definition but we do note that it appears to accord with reality and that others have noted the higher leverage of analogical transfer between ideas as opposed to designed artifacts (Weisberg 2006).

A non-obvious assumption made in the model is that inventive effort increases as the cumulative number of individual operating ideas - IOI_C - increases. This assumption is introduced when we assume that *every* existing IOI undergoes a combination attempt in *each* time step. As IOI_C increases, this means that more combinations are attempted in each successive time step. This assumption is critical to obtaining the exponential time dependence for IOI_C and thus for Q because the growth of IOI_C would be choked off if inventive attempts did not increase over time. Although a rigorous test of this assumption is suggested for further work, we do note support for the assumption in the exponential growth of patents over time (Youn et al. 2014, Packalen and Bhattachayra, 2015)[30]. Approximate support is also given by the roughly exponential growth of R&D spending over time (NSF, 2014) and by the roughly exponential growth of graduate engineers globally[31] over time (NSF, 2014)

[30] Both of these papers show more rapid exponential increases before 1870 and slower but still exponential increases over time from 1870 to the present in the number of US patents.
[31] Other supporting evidence is also possible to see in the NSF material at http://www.nsf.gov/statistics/seind14/index.cfm/overview/c0s1.htm#s2

Table 4.1: Assumptions in models and implications of assumptions

Assumption	Support and testability	Implications to output
1. Differentiation of the idea realm from the artifact realm	Reflects reality, is not testable but instead a definition	Critical to causal reasoning about different rates in different domains
2. That inventive effort increases as IOI_C increases	Testable by number of inventors and inventions over time and well supported for patent numbers for 200 years.	Critical to exponential form of performance vs. time from the combinatorial approach
3. Specific science – technology exchange mechanism	The mechanism is not testable but much deep prior qualitative work is consistent with a mutual assistance idea	Not critical to conclusions since other mechanisms also work
4. P_{IOI} independent of domains	Testable by study of stochastic noise in rates in different domains	Critical to causal reasoning about different rates in different domains
5. McNerney et al. model of the influence of interactions on performance improvement	Testable with independent estimates of d for various domains	Critical to quantitative prediction of variation in rate due to interactions
6. Influence of scaling laws	Possibly testable with enough independent estimates of A_J for various domains	Critical to quantitative prediction of variation in rate due to scaling laws
7. IOI_0 initial value	Not testable, but initiation must involve small numbers	Critical to interpretation of halting start for technological progress
8. Quantitative values of various parameters (P_{IOI}, time step, attempts per time step and R) and other simplifying assumptions	Not testable	Not critical to major conclusions since combinations of value choices are indistinguishable and variation among locations and inventors is a source of noise

A related question important to address is whether the exponential outcome was forced to occur in the model? As explained above, the exponential growth occurs in the model due to the assumption that at time step t every IOI in the pool can combine with another one, making number of newly created IOI at a given time step to be proportional to the number of IOI (IOI_C) in the pool (equation 3.5 in section 3.1.3.2). Is this assumption reasonable? If the model were to account for obstacles to accessing other IOI, such that reduced number of IOIc were available for combination, say *1/m* fraction of *IOIc*, the newly created IOI would be given by $P_{IOI} \cdot IOI_C/2 \cdot 1/m$. This would reduce the rate of growth, but the proportionality with IOI_C still stays, and leads to exponential behavior. A hypothetical condition that could preempt exponential growth occurs if we assume that the number of IOI considered for combination at each time step always remains fixed. This would lead to a fixed number of ideas attempting combination resulting in a linear, rather than an exponential, growth. What mechanisms could enforce this limit? One possible mechanism that could enforce this is if the number of engineers working on inventions (effort) globally remained constant over time. But such restrictions are very unrealistic and the literature cited in the previous paragraph contradict such an assumption. This hypothetical example demonstrates assuming non-proportionality necessitates introduction of restrictive mechanisms whereas proportionality naturally occurs in their absence.

The model assumes a simple exchange between understanding (largely science) and operations (largely technology) as described by Equations 3.13 and 3.14. The details of this mechanism are not testable but in our opinion not critical because other formalisms (based upon differences rather than ratios and based upon units of understanding rather than our choice of reach) lead to results closely similar to ours. Therefore, this assumption also remains unverified but not critical to our conclusions. Moreover, the idea of some sort of mutual exchange between science and technology is widely believed including by those who have closely observed the processes historically.

The next three assumptions in Table 4.1 (#4 through #6) are linked because they all underpin the form of Equation 3.28 - the aspect of the model with the strongest potential for prediction. Assumption 4 is that P_{IOI} is the same in all domains (and for all possible IOI) and we consider this both an important and non-obvious assumption. It is important because if P_{IOI} does vary *systematically* among domains, this could provide an additional mechanism beyond interactions and scaling for explaining the variation in K_J - higher P_{IOI} resulting in higher K_J. Moreover, variation in P_{IOI} among different domains is not intuitively unrealistic. A possible test of the form of equation 3.28 can be made to probe this issue. In particular, equation 3.28 suggests that all of the stochastic variation in K_J should be contained in the K_I term since d_J and A_J are constants. Indeed, any noise in K_I is magnified by the same constants that multiply K_I to give K_J. Thus a careful study of the statistical noise in K_J should find that such noise is proportional to K_J if our assumptions are valid, whereas such noise would be roughly constant (independent of K_J) if all of the changes in K_J were due to changes in P_{IOI}.[32]

Assumptions #5 and 6 are re-statements of the importance our model ascribes to interactions and scaling. Assumption #5 can be tested by study of the rates of performance improvement over a variety of domains where an independent assessment of d_J is made. This research has performed such a test using patent data and the results offer support for the analysis of McNerney et al. that we use in our model (the results from that test were presented in section 3.2 and will be discussed shortly). If scaling laws were found (or derived) for a variety of domains whose rate of progress is known, assumption #6 can also be tested. In this paper, we showed that the factor A is at least 3 times larger for Integrated circuits than for combustion engines. While this is directionally correct since Integrated circuits improve about 7 times faster than combustion engines (Magee et al, 2014), two points do not achieve a rigorous test. One would need to have reliable scaling factors for at least 10 domains with varying K_J to determine whether the model is empirically supported.

The initial value of IOI_0 chosen in the simulation (and the exchange frequency with understanding (α $1/ln\ R$)) is essential to our finding of halting slow growth that can transition to sustained, more rapid growth. Although this finding is consistent with detailed observation as noted above, the result cannot be considered predictive because there is no independent means of assessing IOI_0.

Moreover, lack of a means for independent assessment is true for the simulation results generally (assumption 8). To construct a simple and operational simulation, we have made a number of assumptions, introducing some limitations to the model as well as to the simulation results. First, the model assumes that two pre-existing ideas are sufficient

[32] Recent work by Farmer and Lafond (2015) indeed find that the variation in K_J is proportional to K_J offering strong support to the form of Equation 3.28.

(probabilistically) to create another idea whereas inventions also result from bringing more than two pre-existing ideas together. However, adding such complications to the model and simulation does not change the fundamental findings since the creation of new ideas would still increase as the number of pre-existing ideas increase as long as we still assume an increasing invention effort. Even in those inventions where more than two ideas are required, the steps probably occurs sequentially where two are combined first, and then third one added to make the new idea workable. Second, the parameters in the simulation (assumption 8) are not testable independently so these results in general are not predictive.

It is important to note what is outside the explanatory scope of this model in its current form. Since the goal of modeling effort is to explain the patterns at the domain level (study's unit of analysis), the inventions in a domain have been lumped together and considered as one entity. As the model is not agent-based, it does not distinguish between organizations nor between inventors. For this reason, variations among organizations or among inventors within a domain are not taken into account, and hence the model is not useful to understand organization or individual inventor effectiveness in its current form, and any systematic differences among inventor capability across domains is ignored. Additionally, once IOI are created by any inventor, the model assumes they are instantly available for combinatorial analogical transfer across the pool underlying all domains. Thus, the model does not take into account time delay that can result due to, for example, geography, secrecy and governmental regulations, and hence is not useful for studying such factors' influence in technological change.

This analysis of the assumptions point out that some key assumptions embedded in equation 3.28 have the potential to be empirically tested and thus equation 3.28 could become (depending upon the outcome) potentially reliably predictive. Towards this end, the domain interactions were studied, the results from which are discussed next.

4.3 Discussion of empirical study of domain interactions

4.3.1 Discussion of empirical results

The goal of this empirical study was to test the theoretical finding that interactions gives rise to variation in performance improvement rates of technological domains, and those technological domains associated with higher levels of interactions improve at slower rate than those with lower levels. The normalized count of selected keywords reflecting the notions of interaction as described in literature review (Simon 1969, Suh2001, and Whitney, 1996) was used as a proxy for measure of domain interactions. The analyses of keyword data utilized correlation study to examine whether any regularity could be observed between performance improvement rates and keyword counts.

The first finding of the empirical study is that patents can be useful resources for studying domain interactions, and to our knowledge, this is the first time patents have been used to study interactions. Although techniques such as design structure matrix (DSM) have given some results, available data on domain artifacts is very limited; it is very expensive to develop those matrices; and the reliability of the results is highly dependent on the researcher doing interviews and the knowledge of the people interviewed. Further, it will be very hard, perhaps even impossible, to develop DSM of artifacts that were designed say in 1980. In contrast, patents afford a large objective data set that is both publicly available, and spans long periods (electronic patents available from 1976 to the present). The selected keywords reflect the different types of interactions: component-to-component, component-to-system, side effects, and conflict between functional requirements. Each occurrence of keywords can be seen as a marker of each text section in the patents that discusses an interaction issue. The study was conducted in two stages. The pilot study using 5 domains – battery, capacitors, wind turbines, solar PV power, and computer tomography - was used to assess the feasibility of the technique. Specifically, the study was used for identifying keywords representing interactions, and to determine if any signal for interactions at the domain level could be observed.

In the second study, the study of interactions was extended to all 28 domains. Two correlation analysis approaches were used: first approach assumes a linear relationship between K_J and d_J; the second one assumes a linear relationship between K_J and reciprocal of d_J, as suggested by the model. The finding from these analyses are compared and contrasted here. First, both analyses agree in suggesting that high keyword count of a domain is correlated with a low rate of improvement, an important finding. The analyses, however, are at odds concerning the nature of relationship between normalized count of keywords and performance improvement rates: the first one suggests that it can be described as $K_J = -B_1 \cdot C_{KW}$ (please note the minus sign), the second one suggests $K_J = B_2 / C_{KW}$. In these equations, B_1 and B_2 are constants, and C_{KW} is the normalized count of keywords. Which one is a better description of the relationship? The empirical results do not suggest which one is better. The results from the two are practically equal. Theoretical argument might be helpful here in distinguishing which one might be better.

If the first description ($K_J = - B_1 \cdot C_{KW}$) is the correct one, then there has to be another variable that needs to be negatively correlated with K_J to keep K_J positive (which is how it has been defined). In the equation provided by the model, $K_J = (+/- A_J) \cdot 1/d_J \cdot K_I$, the $(+/- A)$ is positive. Once the interaction term - middle one – becomes negative, the K_J becomes negative, which is not consistent with the definition of K_J. Another possibility is that rate of improvement equation might take this form: $K_J = (+/- A_J) \cdot (K_I - d_J)$. In this form, if K_I is higher than d_J, then K_J remains positive. However, if d_J is sufficiently high it will lead to negative K_J, suggesting that the domain's performance will get lower and lower with time, which is not consistent with empirical observations and the definition utilized in this research. The second description does not suffer from these inconsistencies. Following Wacker (1998), 'power of deduction rules" here, and suggests that the second correlation is a better description of the relationship between rates of improvement and count of keywords reflecting domain interactions.

4.3.2 Limitations of the empirical study of domain interactions

Being the first of its kind in using patents to study domain interactions, this approach has some limitations. First, it was observed that the scatter was quite significant. Although, much of this could be due to missing data on scaling, one other very likely source is due to limited resolution of keywords as a measure of interactions. For example, the same interaction issue may be discussed in two or more places in a patent, yet the current method counts each occurrence as separate interaction issue, which may add to the scatter. Ideally, each interaction should be counted only once.[33] However, this is not so bad as to invalidate the method, since all domains are treated similarly and any discrepancy introduced will be common to all domains. Second, another additional source that possibly aggravates scatter might be use of limited number of patents (100 most-cited patents) for the study. This might be an issue with domains which have low count of keywords, which might be the reason why there is a higher spread of data points at lower count of keywords in the graphs (See Fig. 3.21, 3.23, 3.24 in chapter 3). This study has used only 100 patents in each domain due to the limited resolution of COM technique in its current state. Even after identifying domain patents, the patents need to be read by multiple readers – a time consuming manual process - to ensure that the patents actually belong to the domain. Further, some patents cannot be downloaded electronically due to mistakes in how they were uploaded in the web, and thus need to be manually downloaded, further making it time consuming. Therefore, it is effort intensive to extend the number of patents to higher numbers.

The regression model from this empirical study strongly supports domain interaction parameter as a factor that can lead to variation in improvement rates, where higher interaction parameter leads to lower improvement rates. Further, it also supports the relational form the model predicts.

[33] The fact that same interactions is discussed in multiple places can also be viewed as being an indication of its importance.

4.4 Implications of the model and empirical work

The final mathematical model, equation 3.28 in chapter 3 section 3.1, states that annual improvement rate K_J for a domain is determined by the product of K_I, times the scaling parameter A_J and the reciprocal of the interaction parameter, d_J. According to this result, the last two parameters produce the variation of improvement rates across domains. Domain artifacts embody novel operating ideas that are equally available for such "spillover" by all domains. It is important to note that, according to the model, some IOI are absorbed by multiple domains. During the embodiment process, interactions prevalent in the domain artifacts influence how many inventive ideas can be absorbed. The percent increase in successfully absorbed ideas by a domain artifact is inversely proportional to the average interaction parameter of the domain, d_J. Therefore, domain artifacts with lower values of the interaction parameter will be able to absorb more ideas successfully.

The other factor that is predicted to differentiate domains is performance scaling. Inventive ideas affect artifact performance by modifying the design parameters in domain artifacts. The model indicates that the relative improvement of performance for a given amount of absorbed new operating ideas is governed by the scaling parameter A_J. The examples presented in chapter 3, section 3.1.2.5 illustrated the notion that intensive performance can grow with increase in size for domains where larger is better holds, exemplifying the notion of economy of scale. Additionally, the examples showed that the value of A_J can vary across domains. In particular, for the IC domain (where smaller is better), A_J is apparently at least 3 times larger than for typical larger-is-better domains such as combustion engines.

Consequently, the domains with high A_J and low d_J will be improve the fastest, and domains with low A_J and high d_J will improve the slowest. One pertinent question that can be asked at this point: Is it possible, using first order analysis, to explain the variation in K_J, known to vary from about 0.03 to 0.65 (Magee et al. 2014). This is potentially explainable. We can see that the domain rates vary by a factor of about 20. The reciprocal of count of keywords ($1/d_I$) varies by a factor of about 3 (from about 0.003 to 0.012) whereas the scaling (A_J) varies by a factor of about 6 (~0.5 for IC engine to 3 for Integrated circuits). The product of A_J and $1/d_J$ then varies by a factor of about 18 or higher, which is very close to the variation in empirical K_J. Although the numbers used might not be very precise, they do give a sense of the range of possible performance outcomes as predicted in the model.

A note of caution is necessary here: we have seen that while variation in K_J is potentially explainable by changes in d_J and A_J, much more empirical work is needed to fully support these quantitative implications of equation 3.28.

Another useful implication of equation 3.28 is that if K_1, A_1, d_1 are known for, say domain1, then rates for another domain2 with A_2 and d_2, may be found in reference to domain1. The equation

$$K_2 = K_1 \cdot (A_2 / d_2) \cdot (d_1 / A_1)$$

(obtained by taking a ratio of equation 3.28 written for two domains) makes it possible to calculate the improvement rate for another domain. This eliminates from equation K_I or P_{IOI}, which are challenging, if not impossible, to determine.

Overall, the model qualitatively indicates that the differences in rates of improvement among domains is more "technically based" (A_J and d_J are fundamental parameters for the domain) than usually anticipated. This implies that a domain like batteries (with high d) perhaps cannot be made to improve as fast as optical telecommunications (with low d) by investing the same amount of capital as in the optical telecommunications. We may understand this notion intuitively by thinking of inventions as those that directly lead to improvement of performance (or main functions) and those that are used for mitigating untoward issues, such as side effects, in a domain artifact. Given the same set of resources, the domains with more of those untoward issues will have to create more inventions to deal with those untoward issues, thus draining the resources that could be utilized for generating the performance improving inventions. In contrast, the domains with less untoward issues will be able to generate more of the performance improving inventions. Similarly, domains whose artifacts follow stronger scaling laws (due to the embedded physics) are provided greater leverage towards improving performance for the same inventive effort. Together these two fundamental levers can produce a range of performance outcomes.

If it is instead assumed that non-fundamental variables are the only source of all variation in rate of improvement, missteps will occur. This brings us back to the quote by Katie Fehrenbacker (2012) in chapter 1. She draws attention to the misguided assumption that enough capital and talent can make any technology grow as fast as computers do. She implies that domains might be fundamentally different; our model indicates that those fundamentals include domain interactions and scaling in the specific relationship given by equation 3.28.

4.5 Reflecting on the model: types of theories and "good theory"

This section closes this chapter after reflecting what type of theory has been developed in this research and how the model fares as a "good theory".

The primary goal of this thesis is to develop a theoretical model that examines the nature of technological performance improvement trends. Following the taxonomy of Gregor (2006), theories may be classified into five categories (shown in Table 4.2). Accordingly to this framework, Moore's Law, and even its generalized version, is predictive (Type III) but not explanatory. On the other hand, Dosi's theory of technological paradigm-trajectory, Christensen's theory of disruptive innovation, and other theories of technical change, are type I and II as they describe the structure of innovation and explain why it occurs, but they are not predictive. The goal of this research effort is to advance to type IV theory, that is, to develop a model that is both explanatory and predictive. Towards this end, the exploration utilizes two sets of well-known mechanisms in the design science to provide an explanation conceptually, and takes an analytical mathematical approach to build a predictive model (Wacker 1998).

Table 4.2 A taxonomy of theory types in Information Systems Research. Adapted from Gregor 2006.

Theory Type	Distinguishing Attributes
I. Analysis	Says what is. The theory does not extend beyond analysis and description. No causal relationships among phenomena are specified and no predictions are made.
II. Explanation	Says what is, how, why, when, and where. The theory provides explanations but does not aim to predict with any precision. There are no testable propositions.
III. Prediction	Says what is and what will be. The theory provides predictions and has testable propositions but does not have well-developed justificatory causal explanations.
IV. Explanation and prediction (EP)	Says what is, how, why, when, where, and what will be. Provides predictions and has both testable propositions and causal explanations.
V. Design and action	Says how to do something. The theory gives explicit prescriptions (e.g., methods, techniques, principles of form and function) for constructing an artifact.

Table 4.3 General Procedure for theory-building and the empirical support for theory. Adapted from Wacker 1998.

	Purpose of this step	Common question	'Good' theory virtues emphasized
Definitions of variables	Defines who and what are included and what is specifically excluded in the definition.	Who? What?	Uniqueness, conservation
Limiting the domain	Observes and limits the conditions by when (antecedent event) and where the subsequent event are expected to occur.	When? Where?	Generalizability
Relationship (model) building	Logically assembles the reasoning for each relationship for internal consistency.	Why? How?	Parsimony, fecundity, internal consistency, abstractness
Theory predictions and empirical support	Gives specific predictions. Important for setting conditions where a theory predicts. Tests model by criteria to give empirical verification for the theory. The riskiness of the test is an important consideration.	Could the event occur? Should the event occur? Would the event occur?	Empirical tests refutability

The thesis has utilized four steps described by Wacker (1998) (see Table 4.3) for building a "good theoretical" model. Specifically, the literature review discussed the pertinent variables and unit of analysis, while chapter 3 developed the qualitative and mathematical relationships among the underlying mechanisms, followed by development of empirical support with study of interaction parameter using patents. Here we will reflect on the current model with respect to salient virtues of a "good theory", specifically abstraction, internal consistency, empirical riskiness (testability), generalizability and parsimony. How does the current model fare with respect to these criteria?

According to Wacker (1998), a "good" theory has a higher abstraction level because it integrates many relationships and variable into a larger theory. In other words, it has a higher explanatory power. The analytical model presented in this thesis integrates multiple well-known mechanisms – invention based on combinatorial analogical transfer, mutual exchange between understanding (science) and operations (technology), interactions and scaling - in design research to develop a predictive and explanatory model for technological performance trends. It specifically brings together principles from three different fields - technical change, cognitive aspects of design research, and modeling. It is clear that the model satisfies this criterion well.

Internal logical consistency of the mechanisms integrated together and the variables utilized to build a theory is perhaps the most important virtue. Wacker (1998) mentions that one way to ensure this consistency is by developing mathematical relationships among the variables involved. The current model is an analytical mathematical model. Equation 3.3 in section 3.1 mathematically relates K_J, rate of performance improvement, to sequentially related mechanisms and variables – scaling of design variables, integration of inventive ideas into artifacts and creation of inventive ideas (through cognition), all of which are well explored concepts in the literature. The model determines each derivative in equation 3.3 to obtain the final equation 3.28 in section 3.1 (chapter 3). This equation aspires to be predictive and provides a basis for empirical riskiness (testability).

A "good theory" has to be easily testable, and the more bold it is in terms of predicting, the better. The current model provides at least three variables for testing: A_J

(influence of scaling on variation in domain performance), d_J (influence of interactions on variation in domain performance), and K_I (exponential rate which is a function of P_{IOI}, probability of combination, and exchange between understanding and operations). The second parameter, d_J, was positively tested in this research effort, and for the second, a short exploration was presented. Perhaps, the most challenging one will prove to be testing of K_I. Farmer and Lafond's work on variability of K_J is already paving the way for its test.

Finally, a "good theory" has to be generalizable to more areas. In this respect, the current model has to be applicable to larger number of domains. The current model was initially motivated by the desire to explain the variation in improvement rates seen 28 domains. However, the modeling effort has not utilized any specific domain attributes to build the model; instead, it is based on general design principles and mechanisms that cut across the domains, thus ensuring the generalizability of the model.

The final criterion for "good theory" is parsimony, which relates to minimizing the number of assumptions made in the theory. The previous section 4.2.2 thoroughly discussed the assumptions made and the limitations it introduced in the current version of the model. Although there are not a small number of assumptions, the model may approach the minimum number needed at this point in time.

This discussion has shown that the current model fares well with respect to these crucial elements of a "good theory" with the arguable exception of parsimony. It was also clear that number of assumptions need further research, before the model can be considered fully predictive. Despite this, it is believed that the model and simulation in current form still provide useful, novel findings that support some existing ideas about design cognition and the nature of technological change.

The thesis concludes in the next chapter with the discussion of contributions made by this research effort towards deepening the understanding of technical change, and new research questions it has spawned for future investigations.

Chapter 5: Contributions and Future Research

This chapter presents contributions made by this research effort towards deepening the understanding of technical change, particularly within the sub-field of technical performance change. This will be followed by an enumeration of several questions spawned by this research. Concluding remarks close the chapter.

5.1 Contributions of the research effort

This research effort contributed towards developing a greater understanding of technical performance change in three broad areas: developing a framework and methods for analyzing quantitative technical performance trends, developing an analytical model based on design fundamentals, and conducting an empirical study of interactions, a fundamental feature of technical artifacts.

5.1.1 Contributions in analyzing quantitative technical performance trends

My research group, particularly Chris Benson and I, worked in the area of analyzing the quantitative technical performance as part of our doctoral work. This thesis has described the findings in this research area as part of the literature review. This section describes the contributions made in this area, particularly that of the current author, that has helped to advance the understanding of the technical performance change.

Prior studies of technical change had often used 'off-the-shelf' terminology to describe different technologies. Such terminology often lacked precision in the definition of the unit of analysis and thus introduced significant ambiguity of varying degree. The approach used by Koh and Magee (2006, 2008) utilized functional categories as the unit of analysis; this approach was superior to ad hoc approaches used earlier, since function as a dimension provided a logical framework to categorize and lump different technologies. But this functional approach cast too wide a net, and joined together seemingly unrelated technologies, such as combustion engine, electrical motor, solar PV power, wind power, fuel cells, and incandescent lighting, into a single functional category, energy transformation, although all were used for energy conversion. In order to overcome this issue with low resolution, aside from function, a new dimension – body of scientific and engineering knowledge underpinning the technology – was introduced; this allowed decomposition of functional categories into technological domains, defined as a set of designed artifacts that utilize a body of scientific and engineering knowledge to achieve a generic function (Magee et al. 2014). This decomposition using function and knowledge base provides greater specificity to the unit of analysis, and most importantly, it provides a framework to reduce ambiguity for further research. (If required, it allows further sub-division based on a narrower definition of the relevant knowledge base.) Using these new approaches for definitions of unit of analysis, over 50 technological domains were identified. Several functional categories, such as information storage, were decomposed into multiple domains – magnetic storage (tape and hard drive), optical storage and semiconductor memory.

A second aspect important in this area is use of a suitable performance metrics. This research has adopted the framework of combining multiple desired performance attributes, and resource constraints. Accordingly, a suitable metric for passenger airplanes will include both number of passengers transported and speed of airplane, and time duration as the resource. This approach ensures that improvement in performance along one performance attribute is not achieved through trading-off other performance attributes. This framework aided in culling reported performance metrics that only included one performance attribute or did not include some type of resource constraint (e. g., lowest temperature achieved for cryogenics), and ensured that comparison of performance improvement rates across domains was meaningful. Implementation of these criteria resulted in elimination of many domains, leaving a total of 28 domains with 70 plus metrics.

The third important contribution in this area is the broader consideration of effort variables – production as well as revenue and patents. The study of IC chips demonstrated that each of these effort variables followed an exponential growth and satisfied the Sahal relationship (Sahal 1979, Nagy et al. 2013, Magee et al. 2014). Further, the study of the 28 domains using patents as an effort variable demonstrated that patents do not always follow exponential growth, and the power-law was upheld in only about half of the cases; and yet, the exponential improvement with respect to time was followed in all cases. This suggested that time as an independent variable might be a superior choice for study of performance improvement over generations of designs, although both effort and time as independent variables are adequate for singular designs. The performance trends for the 28 domains against time follow exponential trends, but with rates varying from about 3 to 65% percent. These reliable results formed the basis for further research.

Benson (Benson and Magee, 2015b) empirically investigated the variation of the improvement rates in these 28 domains using meta-characteristics of patents, which are outputs of design and inventive effort. The research work presented in this thesis instead examined the internal dynamics of design and inventive processes underpinning technical change, and developed a predictive and explanatory theoretical model for variation in exponential trends exhibited by the technological domains. The contributions made in the modeling area are discussed next.

5.1.2 Contributions towards deepening the theoretical understanding of technical performance trends

Technical change has often been viewed as occurring inside a black box by researchers in business and economics, and have usually avoided examining design activities as the source of technical change. Recent publications of Baldwin and Clark (2006) and Luo et al. (2014) have begun to build a connection between economics of technical change and design. The research work presented in this thesis has contributed towards expanding this effort by developing a predictive and explanatory theoretical model that utilizes the known mechanisms of design and inventive processes to explain the trends seen in technical performance change, thus making design endogenous to technical change. The model has demonstrated that the design and inventive process is the engine that powers technical performance change.

The model utilizes two sets of known mechanisms in design to explain exponential performance trends with variation in rates among domains. The combinatorial analogical transfer mechanism give rise to exponentially growing pool of operating ideas (over time) in the ideas realm, which can be accessed by all technology domains. The model incorporates mutual exchange between understanding (largely science) and operations (largely technology), each helping to break barriers in the other. To the best of our knowledge, this is the first attempt to include influence of understanding in modeling of technical performance change. The second set of mechanisms - domain interactions and scaling of performance - give rise to variations in performance improvement rates across domains. We adapt and extend the treatment of McNerny et al. (2011) to model the ability of domain artifacts to assimilate operating ideas from the IOI pool, where associated interactions of the artifact determine its ability to exploit the operating ideas in the IOI pool. The assimilated operating ideas change the design variables favorably to increase the performance. The relative performance change for a given change in a design variable is determined by scaling parameters (or scaling of performance). Together, the scaling and interaction parameters (quantifying these two mechanisms) modulate the rate at which operating ideas (knowledge) lead to variation in performance of the artifacts in domains.

The model thus integrates these known five mechanisms (and the theories behind them) of design with technical performance change to develop a theoretical model of a higher abstraction level. Thus, the model has unified the technical change with design research, and deepened the understanding of technical performance, perhaps its most significant contribution.

An important practical implication of this model from a policy and investment perspective is that all sources of variation is not external variables such as R&D investment or expertise, but rather internal domain fundamentals also play a significant role as determinants. Once these internal factors get more empirical support, this insight will expand the toolkits used by policy makers, investors and technology planners and strategists. Opening of this possibility is another contribution of this model.

5.1.3 Contributions from empirical study of interaction using patent data

The design structure matrix (DSM) for artifacts, as discussed in the literature and in the methodology section 3.2, provide detailed descriptions of interactions between components and sub-systems in an artifact, thus making it a desirable method to study interactions. DSMS available in the literature, however, are very limited, especially for those technological domains for which performance data is available. Additionally, DSM for artifacts are very expensive to develop, and may even be extremely challenging to do so for artifacts developed decades ago. To circumvent this challenge, an alternate method of studying interactions using text in patents as the data has been developed. The method utilizes 6 keywords representing interactions, and the normalized cumulative count of these 6 keywords provides a measure of the level of interactions in the domains. Because the method is based on patents, a textual data is objective and is available over a long period of time, with electronic data available for almost 4 decades. Additionally, accessing and analyzing textual data is relatively inexpensive and doable. To our knowledge, this method using patent data to study interactions is the first of its kind, and thus contributes (1) by opening a whole new data source, and (2) by developing a specific method, for studying domain interactions.

The method has enabled comparative empirical study of interactions across domains and how it correlates with performance. Whitney (1996, 2004) had shown why interactions might have fundamental characteristics, and Koh and Magee (2008) had qualitatively argued, and McNerney et al (2011) had modeled that domain interactions impact the performance improvement rates. The model presented in this thesis incorporates McNerney's treatment as an essential component for explaining the variation in rates. However, to our knowledge, no prior independent empirical research exists that supports Whitney's qualitative argument or McNerney's quantitative findings. Utilizing the performance data and textual data from patents for the 28 domains, the study in this research has contributed by providing, for the first time, empirical support for the argument that interactions give rise to variation in performance improvement rates, with higher levels of interactions leading to lower improvement rates. The empirical findings also provide support to the model's prediction that performance improvement rates vary with the reciprocal of the level of interactions.

5.2.4 Empirical study of permanent magnets

The empirical case study of permanent magnetic materials has contributed by developing performance data and identifying set of relevant patents for an additional domain. Using this data, the study independently tested and provided empirical support for two regression models, the first of which predicts performance improvement using patent meta-characteristics, and the second of which correlates performance improvement rates with normalized count of 6 keywords representing interactions.

The discussion above has shown that the contributions have been in three distinct areas, spanning both theoretical and empirical areas. These contributions have deepened the understanding technical performance change and demonstrated that design is the engine that powers technical change. As another contribution, both the model and empirical studies have also spawned many new questions for future research, which are discussed next.

5.2 Future research questions

The predictions and assumptions made by the modeling effort have raised many salient research questions for the future:

- The model has suggested that interaction and scaling give rise to variations in rates of improvement of performance across technological domains. The empirical study in this research has developed support for the interaction parameter as a contributor to such a variation. Does the scaling parameter also contribute to variation in performance improvement rates as suggested by the model? This needs to be assessed empirically independently. Usage of relevant design texts, handbooks, and manuals for each domain, including inventor interviews, might be a potentially good starting point for such an empirical study.

- Another question that naturally arises is whether interaction and scaling parameters together can account for all the variations? If not, what other possible mechanisms could help to explain all the variations? Do non-fundamental variables such as investments in the domains, and inventor effectiveness influence differences in performance improvement rates among domains? If so, how do they come into the dynamics? Are there systematic differences in investment and inventor-effectiveness across domains when considered over a long period? And most importantly, how can objective, empirical studies of these important questions be performed?

- Investigating whether the probability of combination, P_{IOI}, is constant (assumed to be a constant in the model) or varies with domains is an important future question. A potential approach is to study stochastic noise in performance improvement rates along with relevant values of interaction and scaling parameters. The determination of the constancy of P_{IOI} will either support the model or suggest modification.

- An interesting question this modeling work raises is how could this modeling work be extended to understand the growth of design capacity of firms, and nations? Any additional insight on how effective nations develop their design capacity could be helpful for the emerging markets.

The empirical study of interactions using patents, being a first of kind, has much room to be improved, and here we list some suggestions.

- The results from the current empirical study of interactions has significant scatter in the region where domains have low normalized count of keywords. This may be because the current study utilized textual data from only 100 patents for each domain.

Increasing the number of patents used to, say 200 to 300, could give more stable values and thus help to reduce the scatter. To do this without doubling or tripling the reading effort, the effectiveness of the COM technique has to be improved. It would be desirable to eliminate human reading and still get only relevant patents which might be doable by use of natural language processing approaches used in addition to COM.

- The correlation coefficient with a value of −0.56 in the correlation study of performance improvement rates and normalized keywords was modest. One obvious reason as suggested by the model is the absence of the scaling parameter. If the research suggested above makes scaling parameters available, then future research should carry out a multiple regression of performance improvement rates using interactions and scaling parameter values. This should potentially increase correlation coefficient as well as the predictive power of the regression model. The current keyword-based method requires the researcher to determine what words represent interactions in the patents. Whether the same words are used to denote those interactions in new domains, and whether a majority of interactions have been accounted for are legitimate questions. The natural language processing methods such as subject-verb-action (SAO) utilizing contextual meaning might be equipped to handle these concerns once they become more capable. They are also likely to have a better resolution, and may increase the relevancy of the text representing interactions.

5.3 Concluding Remarks

The mathematical model presented in this thesis integrates two sets of known mechanisms in design and inventive processes to explain and predict the exponential trends exhibited by technological performance change. The exponential trends are shown to arise from a simple version of analogical transfer as a combinatorial process among pre-existing operating/inventive ideas. The model is consistent with certain known behaviors of technical change including:

1. The transition from slow, hesitant technological change to more sustained technological progress as technological ideas accumulate;
2. A role for the emergence of the scientific process in stimulating the transition described in point 1;
3. The exponential increase of performance with time (generalized Moore's Law) seen quite widely empirically.

Based on a second set of mechanisms, domain interactions and scaling of performance, the model also indicates that:

4. The rate of performance increase in a technical domain is at least partly (and possibly largely) due to fundamental technical reasons (component interactions and scaling of design variables) rather than contextual reasons (such as investment in R&D, scientific and engineering talent, or organizational aspects).

Numerous modeling assumptions have been made in developing the model but only some of these are critical to the conclusions just listed. Further specific research is suggested to move some critical assumptions into the testable category. The assumptions underlying point 4 have been discussed extensively in chapter 4 and in the previous section. Interactions in domain artifacts, one of the mechanism identified as giving rise to variations, was empirically tested using patents, and the results support the quantitative form of this mechanism in the model. The detailed study of noise in performance improvement rates, and study of scaling parameters need to be carried out in the future, and findings from such research could support or lead to modification of the model.

Appendix A: Supplementary data and results from case study of permanent magnet materials

A.1 Performance data

The Table A.1 summarizes performance data for permanent magnetic materials. Columns 2, 3, 4, 5 provide the raw data, while columns 7 and 8 show data for non-dominated performance, which are 'record-setting' data points.

Table A.1 Permanent magnetic materials: Performance data

						Non-dominated	
#	**Year**	**KJ/m^3**	**Material**	**Source**		**Year**	**KJ/m^3**
1	1917	11.82	Steel	Gutfleisch, O . (2000)		1917	11.82
2	1930	11.82	Ferrite	Gutfleisch, O . (2000)		1931	17.67
3	1931	17.67	Steel	Gutfleisch, O . (2000)		1933	17.83
4	1933	17.83	Steel	Gutfleisch, O . (2000)		1941	41.25
5	1941	41.25	Alnico	Gutfleisch, O . (2000)		1952	53.28
6	1951	35.45	Ferrite	Gutfleisch, O . (2000)		1962	87.45
7	1952	53.28	Alnico	Gutfleisch, O . (2000)		1970	163.46
8	1962	87.45	Alnico	Gutfleisch, O . (2000)		1971	211.31
9	1965	6.0146	Sm-Co	Gutfleisch, O . (2000)		1974	230.42
10	1966	42.156	Sm-Co	Gutfleisch, O . (2000)		1976	245.53
11	1970	163.46	Sm-Co	Gutfleisch, O . (2000)		1978	254.26
12	1971	211.31	Sm-Co	Gutfleisch, O . (2000)		1983	289.66
13	1974	230.42	Sm-Co	Gutfleisch, O . (2000)		1984	333.52
14	1976	245.54	Sm-Co	Gutfleisch, O . (2000)		1985	367.85
15	1978	254.26	Sm-Co	Gutfleisch, O . (2000)		1986	395.16
16	1983	289.66	Nd-Fe-B	Gutfleisch, O . (2000)		1993	427.15
17	1984	333.52	Nd-Fe-B	Gutfleisch, O . (2000)		1998	444.44
18	1985	367.85	Nd-Fe-B	Gutfleisch, O . (2000)		2006	467.2
19	1986	395.16	Nd-Fe-B	Gutfleisch, O . (2000)			
20	1993	427.15	Nd-Fe-B	Gutfleisch, O . (2000)			
21	1998	444.44	Nd-Fe-B	Gutfleisch, O . (2000)			
22	2006	467.2	Nd-Fe-B	Walmar, 2008			
Location of data:							
Folder:							
File:	permanent_magnets_KJ_per_m3_v1_12.22.2013.xlsx						
Sheet:	performance data with sources for sharing						

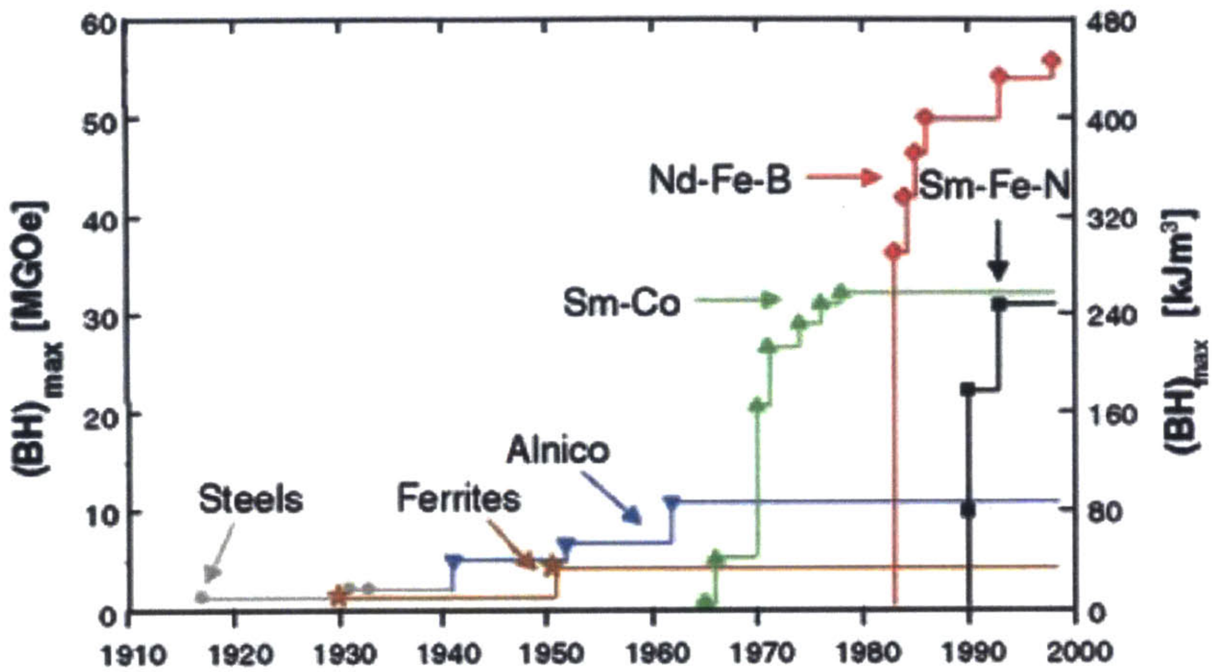


Fig. A.1 Source for performance of magnetic material over time. Adapted from Gutfleisch (2000).

A.2 Patent search for permanent magnetic material using COM

A.2.1 Keywords for patent search

The following keywords were used for searching patents in the seed set using the COM (Classification overlap method):

Magnetic material, permanent magnetic material, hard magnetic material, soft magnetic material.

Using only *'permanent magnet'* gave a lot of patents related to applications of permanent magnetic materials, thus severely diluting the patents that were related only to improvement in intrinsic properties of magnetic materials.

A.2.2 MPR calculations

Table A.2 MPR calculations for IPC classes

	from KW search only, pat count	from KW search ^ within class	In pat class	MPR
H02K	3896	1528	52719	0.21059
H01F	3896	829	37161	0.117545
C22C	3896	97	29057	0.014118
G01R	3896	91	113931	0.012078

For UPC classes:

Table A.3 MPR calculations for UPC classes

Type of UPC classes	# pat (KW search only)	# pat (KW search ∩ UPC class)	Pat # (in UPC class)	MPR
310	3896	831	67060	0.112844
335	3896	452	16503	0.071703
148	3896	200	33665	0.028638
29	3896	139	277205	0.01809
324	3896	94	97936	0.012544
210	3896	88	81980	0.01183
420	3896	78	14527	0.012695
251	3896	41	35098	0.005846
204	3896	35	58988	0.004788
428	3896	32	221007	0.004179

It has be noted that use of only MPR values to decide on the combinations of UPC and IPC was hard to accomplish and was taking longer than anticipated. For example, combination and 310 and HO2K was giving a lot irrelevant patents. Aside from the MPR values, the examination of the description of IPC and UPC classes expedited the process in terms of pinpointing the appropriate sub-class for UPC.

A.2.3 Summary of IPC and UPC classes used in COM for obtaining patents

The overlap of IPC class HO1F and two UPC classes 420 and 302/335 were used for obtaining the patents for the permanent magnetic materials domain. Tables A.4 describes what these classes include.

Table A.4 Description of UPC and IPC classes used for permanent magnetic materials

	Classes	Type	Description
1	420	UPC	Alloys or metallic compositions
2	335	UPC	Electricity: magnetically operated switches, magnets, and electromagnets
3	302	UPC	.. Permanent magnets: (this is a sub-class within 335)
4	H01F	IPC	Includes magnets; inductances; transformers; selection of materials for their magnetic properties [2][34]

The classes shown in the Table A.4 were used in following search criteria in PatSnap for retrieving patents this domain:

(CCL:(420 OR 335/302)) AND ICL:(H01F) AND (APD:[1976-7-1 TO 2013-7-1])

It has to be noted that patents were obtained from January of 1976 till July of 2013.

This resulted in 1321 patents, with a relevancy of 74%. The patents considered irrelevant were mostly related to applications of magnetic materials, rather than reflecting innovation

[34] Description of H01F available at
http://www.wipo.int/ipc/itos4ipc/ITSupport_and_download_area/20140101/pdf/scheme/full_ipc/en/ipc_en_h_full_ipc_20140101.pdf

in magnetic material properties. Two researchers, including the current author, read the patents.

List of 100-most cited patents retrieved from PatSnap:

The patents are listed in descending order with respect to number of citations they have received.

US4770723,US5631093,US6927657,US4402770,US4792368,US4802931,US4056411,US4668310,US4881989,US5049208,US4496395,US5345207,US4374665,US5022939,US4684406,US4126494,US4851058,US4231816,US4689163,US4994777,US4935080,US4981532,US4985089,US4110718,US5252148,US4836868,US4770702,US4150981,US4152144,US4614930,US4378258,US4620872,US4438066,US4664724,US4225339,US4323629,US5034146,US4038073,US5334267,US6048601,US4409043,US4773950,US4623387,US5976715,US5522948,US4767474,US4888512,US4004167,US5069731,US6525634,US4547758,US4765848,US4318738,US4075042,US5522946,US4053331,US6747537,US5992006,US4093453,US4185262,US3899762,US7148777,US4983232,US4814053,US4284440,US4588439,US4081298,US6172589,US6648990,US4600555,US4998976,US5858123,US4840684,US7175718,US4192696,US3982971,US7498914,US5817191,US4935074,US5230751,US6296720,US5549766,US6302972,US5350628,US4289549,US6563411,US4116727,US5019796,US3784945,US5367278,US5888416,US6280536,US4952239,US5645651,US4849035,US4969963,US4678634,US7286034,US4591817,US5750044

A.3 Regression models

A.3.1 Based on patent meta-characteristics

The regression model from C.L. Benson's thesis:

$$K = -31.1968 + 0.1406*cit3 + 0.0155*AvgPubYear$$

Where cit3= number of citations in first 3 years, and AvgPubYear = average publication year

The table A.5 shows meta-characteristics for the permanent magnet materials along with predicted and observed improvement rates. Fig. A.2 and A.3 show the meta-characteristics overlayed with those of 28 other domains. Both suggest that the predicted rate will be low.

Table A.5 Patent meta-characteristics				
Citation in first 3 years	Avg. pub year	relevancy	Predicted *K*	Observed *K*
1.75	1999.59	~74%	4.3%	4.86 %

Location: Dropbox\Patent Set Downloads 8.4.13\103 - 4th set of domains\62 - Permanent magnets; File: 420_OR_335-302_AND_H01F.xlsx; Sheet: search_summary

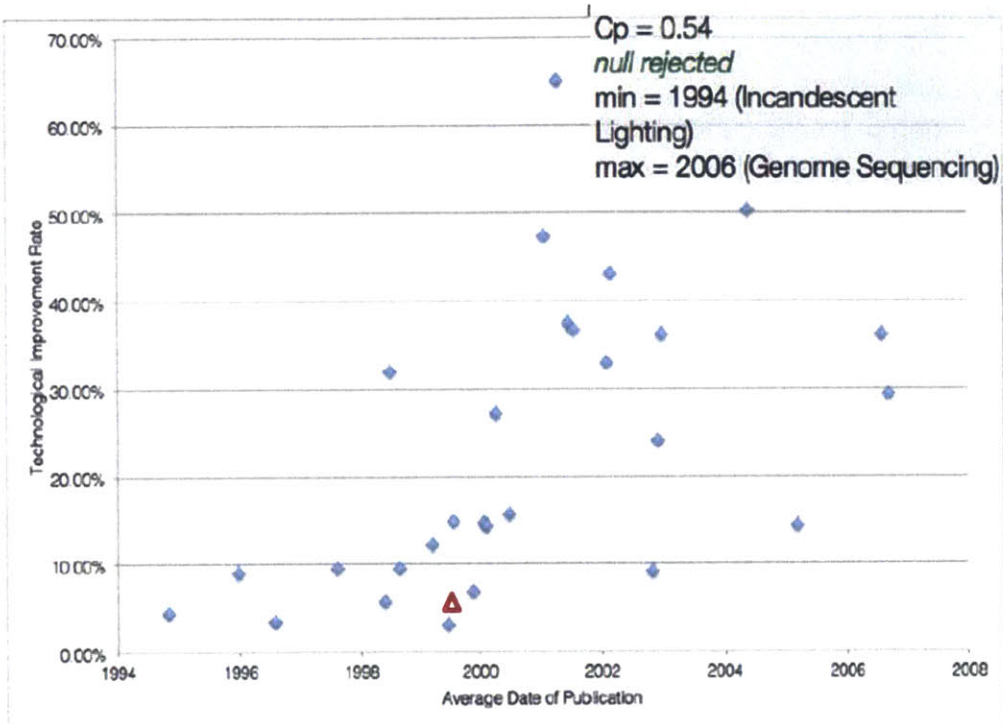


Fig. A.2: Permanent magnet's average publication year superimposed over those for 28 domains. Graph adapted from Benson 2014.

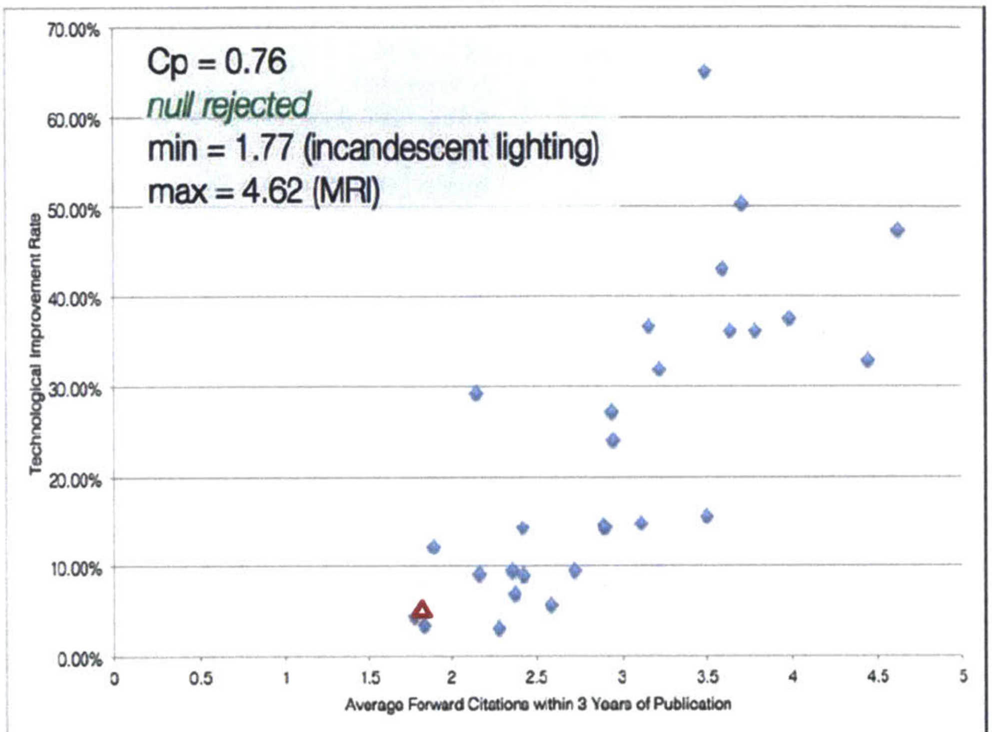


Fig. A.3: Permanent magnet's citation received within 3 years superimposed over those for 28 domains. Graph adapted from Benson 2014.

A.3.2 Regression model II: Based on keywords representing interactions

The regression model is based on the empirical study of interactions presented in section 3.2

$$K_J = -0.1897 \cdot count_{keyword} + 50.575$$

Where $count_{keyword}$ is the normalized count of 6-keywords for every 100 thousand words in the text. The tables A.6 and A.7 tabulate the count of each keywords and the normalized count of 6-keywords. With a normalized count of 6-keywords, the predicted value is 24%.

Table A.6: Count of 6-keywords			
Keywords	**Count**	**Total words without stop words**	**Normalized 6KW/100000 words**
Prevent	16		
Undesir	4		
Requirement	13		
Fail	7		
Disadvantag	28		
Overcom	10		
Total count of KW	75	53571	140

Table A.7 Predicted and observed values		
Normalized count of 6KW	**Predicted *K***	**Observed *K***
140	24%	4.86 %

Appendix B: Supplementary results from empirical study of domain interactions

Appendix B documents two sets of results from two text mining approaches used in the pilot study. The first set presents exploratory results from LSA and LDA, which were not fruitful. The second set presents supplemental data and results, not presented in section 3.2.

B.1 LSA and LDA text mining results from pilot study

Latent Semantic Analysis (LSA) and Latent Dirichlet Analysis (LDA) were explored initially as text mining for obtaining domain interactions, since they do not require expert knowledge. See section 2.4.5.3 for further description of these techniques. If successful, they would have been potentially more objective. Some exploratory results as samples are presented below. Both of these techniques as well as the keyword based technique used patent text from 5 domains - battery, capacitor, wind turbines, solar PV, and CT scan.

B.1.1 Results from LSA analysis

LSA decomposes the word-document matrix (where each entry in the matrix is the frequency of a specific word (row) in a specific document (column)) using singular value decomposition. The diagonal matrix provides the distribution of eigenvalues over the documents. These eigenvalues are plotted over the dimensions, set equal to 100 documents, which in this case are the patents of each domain. The model presented in thesis has suggested that higher level of domain interactions is associated with lower performance improvement rates. Thus, the conjecture was that slowly improving domains would exhibit broader distribution of eigenvalues, indicative of potentially higher interactions.

The 5 domains in increasing order of performance improvement rate (K) are battery, wind power, solar PV, capacitor and CT scan with the rates ranging from 7 to 37%.

According to the conjecture, domains such as bettery should show broader distribution whereas the domain such as CT scan should show a narrower distribution. Fig. B1 shows no clear trends distinguishing the domains. Infact, four domains, excluding wind power, practically superimpose each other across the 100 patents. Conversation with other researchers who had used LSA in their suggested that LSA might not be sensitive enough to glean information on interactions as they were very specific. Another competing technique, LDA, was explored next, results from which are presented next.

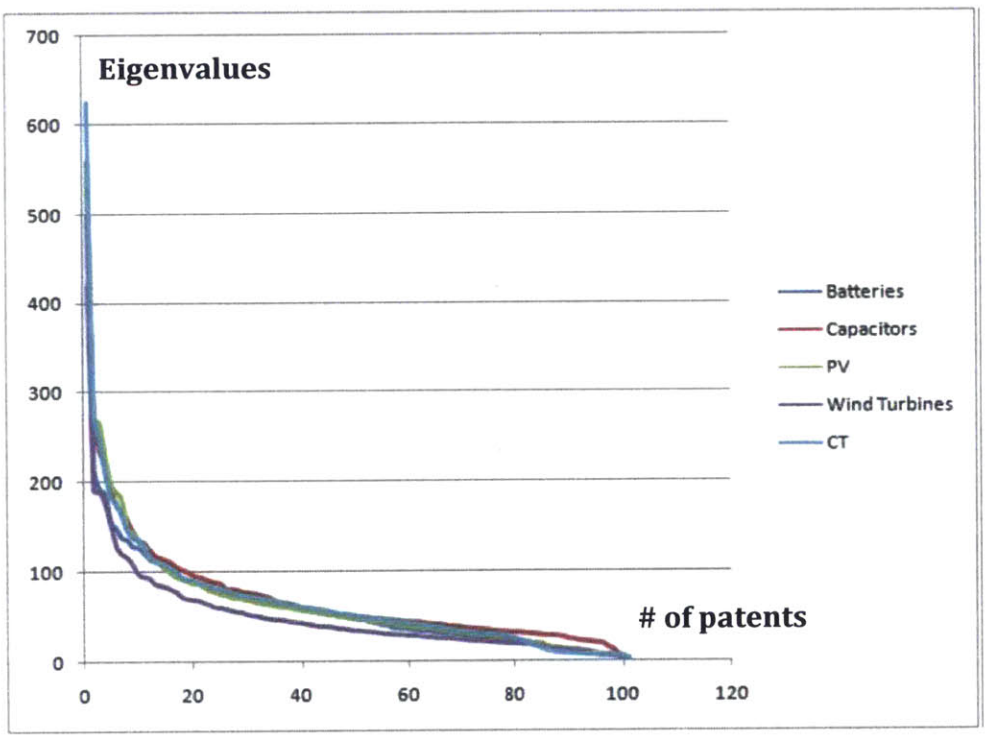


Fig. B.1: Distribution of eigenvalues over the 100 patents for 5 domains.

B.1.2 Results from LDA analysis

LDA, as explained in section 2.4.5.3 decomposes word-document matrix two matrices in order to determine the topics latent in the word-document matrix. First matrix provides the topics (column) distributed over the words (rows). The conjecture in the study was that the topics might provide signal for the interactions latent in the word-patent matrix for each domain. The table B.1 shows the results from such a decomposition for batteries domain with the assumption of 10 latent topics. Consider topic 3(column 3). The occurrence of words such as *cathode, anode, electro-chemical, and electrolyte* suggest that the topic is related to batteries. The fact that patents belong to battery domain and one of the topic suggested by LDA is related to batteries indicates that the technique is able to extract underlying latent topics successfully. Although this is the case, none of the topic columns provide any hint of interactions as discussed in section 3.2.1.4, specifically side effects, functional requirement conflicts, or component-to-component or component-to-system interactions.

The signal from both LSA and LDA as shown were non-existent, hence both of these approaches were dropped from further research. Keyword-based approach was explored, and found to be fruitful. The specific data and results not presented in section 3.2 will now be presented.

Table B.1: Topic word matrix from LDA analysis Batteries domain using 100 patents. **Assumed to have 10 topics, period: sentence, N = 10000 (nb of words: 6267, nb of sentences: 6530, alpha = 10, beta = 0.1)**

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
'laminated'	'formulated'	'invention'	'materials'	'laminated'	'metal'	'fitting'	'laminated'	'preform'	'completion'
'formulated'	'completion'	'cathode'	'charge'	'activatable'	'active'	'parallel'	'formulated'	'parallel'	'machine'
'activatable'	'welded'	'anode'	'discharge'	'completion'	'liquid'	'shorting'	'activatable'	'shorting'	'welded'
'completion'	'seal'	'present'	'hydrogen'	'machine'	'sulfur'	'resists'	'completion'	'resists'	'seal'
'machine'	'feedthrough'	'solid'	'reaction'	'welded'	'preferably'	'stray'	'machine'	'stray'	'feedthrough'
'welded'	'preform'	'provide'	'pat'	'seal'	'alkali'	'projects'	'welded'	'projects'	'insulate'
'feedthrough'	'fitting'	'electrochemical'	'conductivity'	'feedthrough'	'compound'	'opening'	'feedthrough'	'opening'	'preform'
'insulate'	'parallel'	'state'	'temperature'	'insulate'	'conducting'	'pouch'	'insulate'	'pouch'	'fitting'
'preform'	'shorting'	'current'	'storage'	'preform'	'preferred'	'faces'	'preform'	'faces'	'projects'
'fitting'	'resists'	'method'	'ionic'	'fitting'	'group'	'medical'	'fitting'	'medical'	'opening'
'parallel'	'stray'	'object'	'type'	'parallel'	'salt'	'promote'	'parallel'	'promote'	'pouch'
'resists'	'projects'	'electrolytes'	'capacity'	'shorting'	'composition'	'circuits'	'shorting'	'facilitates'	'medical'
'stray'	'opening'	'collector'	'electrical'	'resists'	'form'	'avoids'	'resists'	'largely'	'avoids'
'opening'	'faces'	'electrolyte'	'art'	'stray'	'comprises'	'largely'	'stray'	'chosen'	'facilitates'
'pouch'	'promote'	'elements'	'polymers'	'opening'	'radiation'	'chosen'	'projects'	'outer'	'chosen'
'faces'	'avoids'	'improved'	'temperatures'	'pouch'	'oxide'	'outer'	'opening'	'outermost'	'unidirectionally'
'promote'	'outer'	'composite'	'prior'	'faces'	'include'	'outermost'	'pouch'	'unidirectionally'	'length'
'circuits'	'outermost'	'assembly'	'reduction'	'medical'	'organic'	'unidirectionally'	'faces'	'length'	'establish'
'avoids'	'unidirectionally'	'relates'	'oxidation'	'promote'	'element'	'length'	'medical'	'establish'	'fold'
'facilitates'	'establish'	'generally'	'range'	'circuits'	'polymeric'	'establish'	'promote'	'fold'	'superimposing'
'largely'	'fold'	'background'	'greater'	'avoids'	'mixture'	'fold'	'circuits'	'superimposing'	'shorter'

B.2 Keyword-based text-mining for domain interactions

B.2.1 Patents used for the empirical study

The patents used in the empirical study presented in this thesis were prepared as part of C.L. Benson's doctoral work, in which the current author had been involved in reading the patents. C. L. Benson's thesis (2014) presents the IPC and UPC classes (identified with the COM technique) used for retrieving the patents for each specific domain from the PatSnap database. See pages 312 – 355 in for further details. These retrieved patents were granted during the period from Jan 1, 1976 to July 1, 2013.

B.2.2 Retrieval of patent text from Google's website

The PatSnap database provided the meta-data for each patent but did not provide text in searchable form. The text for each patent, therefore, was downloaded from Google's website using the web-scraping tool developed for this purpose.

The terms used for identifying the headers for the four different sections in the Google patents are listed in Table B.2. Since sections heading for background and summary do not follow any standard, the search terms had to accommodate for many variants, making the development of the tool time consuming, and challenging. The summary section was more challenging mainly because there is another section called the 'detailed description'. Using the custom-built web-scrapping tool, 2421 patents were successfully downloaded, while 371 had to be downloaded manually.

Table B.2: Search terms used for identifying the sections in the Google patent database		
	Section name	**terms used for searching section headers**
1	Title	'Patent-title' 'Invention-title'
2	Abstract	'Abstract'
3	Background (for exact match in heading)	'description of the prior art', 'background of the invention', 'background', 'background information', 'prior art', 'introduction to the invention'
	Background (for partial match in heading)	'.*background.*', '.*prior art.*', '.*related technology.*', '.*related art.*'
	Background (for partial match in paragraph)	'.*background.*', '.*prior art.*', '.*related art.*'
4	Summary (for exact match in heading)	'summary of the invention', 'statement of the invention', 'general description of the invention', 'brief description of the invention', 'short description of the invention', 'brief description of the present invention'
	Summary (for partial match in heading)	'.*summary.*'
	(for partial match in paragraph)	'.*summary.*', '.*statement of the invention.*', '.*general description of the invention.*', '.*brief description of the invention.*'

B.2.3 Results

The total of 2776 patents were included in the study, with 97-100 patents in each of the 28 domains. Python code parsed and counted the number of words in the text for each patent and for the domain as a whole. This data was necessary for normalizing the count of keywords. Similarly, the 8 keywords deemed to reflect domain interactions were counted in each patent and domain as a whole. Table B.3 summarizes the extracted count and normalized count of 8 and 6 keywords.

Table B.3: Summary from data from empirical study of interactions in 28 domains. Columns 1 and 2 identify the domains; column 3 lists number of patents used in domains; columns 4-11 list count of 8 keywords, followed by cumulative count of 8 and 6 keyword for each domain; columns 14 lists words in each domains, then followed by normalized count of 6 keywords, and performance improvement rate (K). The 6 keyword count excludes the count of keywords *'parasitic'* and *'problem'*.

			Count of each keyword												
Domain #	Domain name	# of patents	Prevent	Undesirable	Requirement	Fail	Disadvantage	Overcome	Parasitic	Problem	8KW, total	6KW, total	words, total	(6KW/ Words) * 100000	K%
Domain_1	3DPrinting	100	47	14	31	11	45	14	0	153	315	162	172952	94	38
Domain_2	Aircraft	100	88	14	81	99	48	24	5	108	467	354	131060	270	12
Domain_3	Batteries	100	75	8	48	28	18	15	4	113	309	192	111825	172	7
Domain_4	Camera Sensitivity	99	58	3	34	3	25	19	10	135	287	142	129106	110	16
Domain_5	Capacitor	100	54	23	30	25	32	16	13	121	314	180	117888	153	15
Domain_6	Combustion	99	69	12	23	41	22	22	0	101	290	189	112038	169	6
Domain_7	CT scan	100	31	16	21	14	32	23	0	119	256	137	151289	91	37
Domain_8	Electric Power Transmission	100	42	15	48	28	32	13	88	122	388	178	115704	154	15
Domain_9	Electric motor	99	66	20	29	13	42	21	0	71	262	191	95661	200	3
Domain_10	Electric Telcom	100	88	9	36	25	26	16	0	102	302	200	102817	195	10
Domain_11	Electronic Computation	99	33	0	58	62	19	9	0	219	400	181	146260	124	33
Domain_12	Flywheel	100	48	11	39	80	54	23	3	94	352	255	107438	237	9
Domain_13	FuelCell	99	108	14	73	11	28	17	20	134	405	251	146123	172	14
Domain_14	Genome sequencing	99	42	2	16	7	21	13	1	81	183	101	191484	53	29
Domain_15	Incandescent Lighting	100	63	15	21	62	42	14	0	65	282	217	109610	198	5
Domain_16	LED	100	53	7	12	16	29	17	2	121	257	134	119257	112	36
Domain_17	Magnetic storage	99	64	7	43	17	26	29	0	129	315	186	139223	134	32
Domain_18	Milling Machine	97	89	16	28	22	37	28	0	83	303	220	103482	213	3
Domain_19	MRI	98	21	14	24	17	58	20	6	88	248	154	138033	112	48
Domain_20	Optical Storage	99	72	3	19	34	31	9	0	131	299	168	152731	110	27
Domain_21	Optical Telcom	99	40	7	31	6	23	22	2	120	251	129	106801	121	65
Domain_22	Photolithography	98	33	27	31	11	13	14	1	175	305	129	139494	92	24
Domain_23	Semiconductor storage	97	41	7	28	30	47	21	3	126	303	174	132235	132	43
Domain_24	SolarPV	98	59	11	42	25	22	13	1	89	262	172	128842	133	10
Domain_25	Superconductors	100	41	14	20	11	15	19	3	73	196	120	109385	110	10
Domain_26	Wind	99	39	8	31	29	34	29	0	104	274	170	129593	131	9
Domain_27	WirelessTelcom	99	52	8	60	19	33	29	0	141	342	201	147087	137	50
Domain_28	z_ICs	99	44	11	54	13	37	14	10	128	311	173	110844	156	36

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