TECHNOLOGICAL INVENTION AS RECOMBINANT SEARCH

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ABSTRACT

This paper provides an exploration of some of the implications of inventors using a recombination search heuristic for the process of technological invention. Initially a critical discussion of the literature regarding technological innovation is provided. It is posited that much of this literature adopts a biological perspective, metaphorically employing ideas of recombination, natural selection, punctuated-equilibrium and speciation. Following a tradition of conceptualising technological innovation as a search process, the concepts of a search-space and a technology landscape are discussed. Drawing on Olsson and Frey (2001), a formal model is then proposed. It is demonstrated that a recombinant process creates a convex set of inventive possibilities. The model provides a clear distinction between 'normal science' and paradigmic shifts, the former representing the elimination of non-convexities in a technological set, whereas the later serve to re-introduce them. The model also provides an explanation for the prevalence of local search by inventors, when the cost of search is assumed to be related to the distance between the technologies being recombined. Finally, the model is extended by considering the implications of the sampling nature of technological invention. Kauffman's NK model which describes general properties of certain systems of interconnected components, is utilised in order to provide insight into the likely effectiveness of a sampling process for gaining understanding of the profit potential of untried technological combinations.

Keywords: *Invention, Recombination, Technology Space, NK model*

JEL Classification: O29 - O31

1. INTRODUCTION

The significance of technological invention as an evolutionary engine for economic growth and in shaping intra and inter-organisational structure has long been recognised (Schumpeter, 1934, 1943; Nelson and Winter, 1982; Abernathy and Clark, 1985). Multiple aspects of technological innovation have attracted research interest. Three tributary streams of literature include:

- Economics (Nelson and Winter, 1982), focusing on questions of economic growth and industrial development

- Studies of the influence of firm structure, culture and environment on innovation processes in firms (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Henderson and Clark, 1990)

- Studies of the relationship between innovation and industry competition/structure (Porter, 1996; Nelson and Winter, 1982)

Related streams of literature include that on organisational learning (Levinthal and March, 1981, 1993; Levitt and March, 1988; Cohen and Levinthal, 1989, 1990; March, 1991; Simon 1991) and in recent times, an expanding contribution from the complexity sciences (Levinthal and Warglien, 1999; Lobo and MacReady, 1999; Kauffman, Lobo and MacReady, 1998; Fleming and Sorenson, 2001).

This paper is most closely influenced in spirit by the literature of evolutionary economics, in particular, Schumpeter's view of innovation as the driving force of 'creative destruction'. Schumpeter (1934, 1943) argued that economic development arose primarily from *recombinations* of existing technologies and productive assets, driven by the desire for monopoly profit. Schumpeter distinguished five outcomes of these recombinations (Schumpeter, 1934, p. 66)

- New goods
- New production methods
- Opening of a new market
- New source of supply of raw / intermediate goods
- Creation of a new structure in an industry (for example, the breaking up of a monopoly)

This paper focuses attention on the first of these, the creation of new goods. It is argued that the development of novel goods is primarily a process of recombination of existing technological fragments. These recombination events represent a search operator on a suitably defined technology landscape. A formal model of recombinative search is presented.

1.1 Defining Technology and Invention

In considering the nature of 'technological invention', a precise definition of both terms is required. Innovation is distinguished from invention. Invention has been defined as the act of '*designing and / or creating something which has never been made before*' whereas innovation is defined as the act of '*introducing changes and new ideas*' (Cambridge International Dictionary of English). Although the definitions have some overlap, the key distinction is that of introducing or in a business setting, *commercialising*, changes. An innovative act impacts directly on a product or process, an invention merely has the potential to do so (Abernathy and Clark, 1985, p. 6).

Tushman and Anderson (1986), in a definition borrowed from Rosenberg, define technology as

> *'…tools, devices and knowledge that mediate between inputs and outputs (process technology) and or that create new products or services (product technology)' (p. 440).*

and Levinthal and March (1981) define technology as

> *'…any semi-stable specification of the way in which an organization deals with its environment, functions and prospers' (p. 307).*

noting that this definition includes but is not limited to a traditional microeconomic production function. Kauffman, Lobo and MacReady (1998) refer to a '*production recipe*' (p. 1), with a change in technology leading to a new recipe. The common thread running through these definitions is that of a production function. The Cambridge International Dictionary of English defines technology more broadly as *'the study and knowledge of the practical industrial, use of scientific discoveries.'*.

For the purposes of this paper, the term *'technological invention'* is defined as *'the act of designing / creating novel physical goods'*. These goods are considered to consist of a series of components. The focus of attention is placed on the process of technological discovery, rather than on commercialisation, and attention is restricted to physical inventions as distinct from the creation of new ideas. It is recognised that this definition could contain elements of innovation, however the construction of mutually exclusive definitions of the terms when discussing physical inventions is problematic. Intuitively, the inventions of interest are those which meet a novelty requirement rendering them capable of patenting.

Under the adopted definition, an invention may and usually will, utilise perhaps longstanding prior inventions. Hence, invention is considered to take place, either when a new component is uncovered or in a Schumpeterian fashion, when existing components are recombined in a new way. This latter concept has close parallel with Henderson and Clark's (1990) '*architectural innovation*'. Henderson and Clark (1990), drawing a distinction between innovation of physical components and innovation of the architecture of the connections between these components, classified four distinct forms of product innovation (**Figure 1**).

		Core [Design] Concepts	
		Reinforced	*Overturned*
Linkage between core concepts and components	*Unchanged*	Incremental Innovation	Modular Innovation
	Changed	Architectural Innovation	Radical Innovation

Figure 1: Henderson and Clark's (1990) framework

In this framework, architectural innovations are those which change the architecture (structure of linkages between components) of a product without changing the components themselves, whereas modular innovations are those which alter core design concepts but do not require innovation at a component level. An example of this would be to redesign a fan so it utilised an alternative (non-electric) source of power. There are plausible reasons for supposing that organisations (and individual inventors) will predominantly engage in local technological search, bounded by current architecture (March, 1991; Simon, 1991). As engineers and designers build up experience with the current architecture and components, they will draw on this experience when faced with future decisions rather than re-examining all possible alternatives.

1.2 The landscape metaphor

The landscape metaphor (‘*surfaces of selective value*’) was first introduced by the geneticist Sewell Wright in 1932. The metaphor sought to provide a visual interpretation of the evolutionary adaptation of a biological species to its environment. Evolutionary adaptation was considered as comprising a search on a ‘*landscape*’. The base of the landscape is defined by a species’ genetic composition and the height of the landscape at a given point, corresponds to a measure of the ‘fitness’ or [reproductive] success of the species defined by that specific genetic composition. In this framework, biological evolution represents a search over a genotypic space in a effort to enhance phenotypic fitness. Abstracting the idea of a landscape from an evolutionary setting, it can be applied whenever the outcome from a process is dependent on several inputs. The basic premise underlying the conceptual framework developed in this paper is that the process of invention consists of inventors searching on a suitably defined ‘*technology landscape*’.

The appropriateness of any metaphor or analogy for a given setting must be carefully considered before it can be usefully applied. The utility of a metaphor

> *‘…all depends on whether the similarities the metaphor captures are significant or superficial.’* (Simon, 1996, p. 173)

To the extent that the metaphors assist rather than hinder understanding, their application can be useful. It is noted that the conceptualisation of invention and innovation as a search process is well-developed (March 1991; Simon, 1996; Fleming and Sorenson 2001). Implicitly, this assumes a search-space, a landscape.

1.3 Motivation for paper

The motivation for this paper arises from the challenge posed by technological change to individuals, organisations and societies. Foster and Kaplan (2001) note that the expected tenure of a company on the S&P 500 listing as at 1998 was only 10 years.
Despite the importance of the inventive process as a forerunner of technological change, relatively little attention has been paid to it. The occurrence of inventions has typically been treated as a ‘black box’ in economics, being represented as random sampling from a fixed distribution of possibilities (Kauffman, Lobo and Macready, 1998). This paper attempts to open this box, and provide insight onto the role of recombination in the process of invention.

1.4 Structure of paper

This paper is organised as follows. Section two reviews a selection of the literature on technological invention / innovation and in section three a formal model of invention as recombination is proposed. Only a small fraction of the possible number of recombinations are ever constructed. Whether a sampling process leads to a good understanding of the inventive possibilities depends on the topology of the underlying technology landscape. Kauffman's NK model, discussed in section four provides a useful model for considering the 'ruggedness' or topology of this landscape. Section five provides a short discussion and concludes this contribution.

2.0 LITERATURE REVIEW

This section provides a discussion of the nature of technological change. The dominant strand of literature adopts biological and evolutionary metaphors. By way of comparison, two perspectives on innovation / invention, drawn from the complexity sciences are provided. Next follows a subsection on invention as search.

2.1 Nature of technological change

Technological change can be considered to exist on a spectrum ranging from gradual to sudden and discontinuous. At one extreme, technological change is viewed as gradual, wherein the adaptative process:

> '*…acts solely by accumulating slight, successive, favourable variations, it can produce no great or sudden modification; it can act only by very short and slow steps.*' (Darwin, 1859, p. 444).

As a counter-point, a discontinuous or *punctuated-equilibrium* perspective (Gould and Lewontin, 1979) can be advanced. This suggests that technological invention usually consists of *normal science* (Kuhn, 1996) within a technological paradigm. Periodically this paradigm is shattered or punctuated by dramatic technological inventions. This concept of technological change has a long pedigree. Schumpeter's '*perennial gale of creative destruction*' (1943, p. 86) emphasises major, discontinuous innovations. Tushman and Anderson (1986) adopt a similar argument

> '*technological progress constitutes an evolutionary system punctuated by discontinuous change*' (p. 440).

Several plausible explanations exist to support a punctuated-equilibrium perspective. Punctuations may occur due to a technological breakthrough (invention of a new component[1]) or because of an architectural innovation (a new way of combining existing components[2]) (Henderson and Clark, 1990). Levinthal (1998) argues that punctuation could arise from a *speciation* event, such as when an existing technology

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[1] This view is paralleled by the '*saltation*' argument in evolution. Saltation is the belief that evolutionary change is primarily the result of the sudden origin of radically new kinds of individual that in turn parent a new line of organisms. Most evolutionists strongly reject this claim (Mayr, 2001).

[2] Recombination rather than mutation is accorded the central role in evolution, '*Even though all new genes are produced by mutation, most of the phenotypic variation in natural populations that is available for selection is the product of recombination.*' (Mayr, 2001,p. 98)

is introduced to a new application domain. The speciation concept is drawn from biology where it is proposed that under the right circumstances, a biological population could be rapidly replaced by a *deme* (a localised population) corresponding to an existing niche variant of a wider population (Dawkins, 1986). Levinthal (1998) proposed that a technological innovation initially gets a foothold in a specialist niche in which it has a significant selective advantage, perhaps because the technical requirements of that niche differ slightly to those of the wider market[3]. Due to its promise, the innovation is developed rapidly in this niche and as a result of this development, emerges into a wider application domain. Thus, major technological discontinuities may arise from *a speciation rather than a specific innovative event.* Levinthal's argument can be considered as a re-interpretation of Schumpeter's (1934) view of innovation as resulting from a recombination process, where the relevant recombination is not that of separate technology fragments within an application domain, but rather the recombination of technology from one application domain into another. In summary, the gradualist and punctuated-equilibrium arguments can be distinguished according to the importance they place on incremental invention in explaining the process of technological change.

Although the application of biological and evolutionary metaphors in discussions of technological innovation and invention are common, important differences between the two domains must be recognised. There are distinct differences between biological and technological adaptation relating to direction (teleological) mechanisms, the source of selection criteria and the possibility of Lamarckian processes (Nelson and Winter, 1982). Typically in the application of biological metaphors, it is pointed out that no claim is made that organisations or populations of organisations, behave like biological entities, rather the claim is that an evolutionary perspective provides a general conceptual framework which if appropriately tailored, may provide insights into adaptation processes of individual organisations or of populations of organisations (Singh and Lumsden, 1990; Hannan and Freeman, 1977).

2.2 Complexity perspectives on innovation

Recent years have seen the introduction of concepts from the complexity sciences in an attempt to better understand the nature of technological invention and innovation. Kauffman (2000) speculates that unpredictable outcomes from technological inventions may result from the properties of the complex system[4] within which they are created. Two concepts from the complexity sciences are briefly considered here, *self-ordered criticality* and Kauffman's *grammar.*

The common belief that major outcomes must arise from major causes was challenged by the development of the theory of self-ordered criticality (SOC) (Bak, Tang and Wiesenfeld , 1988). This theory suggests that open dynamic systems, with many degrees of freedom

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[3] Mayr (2001) makes the same argument for biological evolution. The key component of speciation is the existence of an 'isolating mechanism'. This may arise due to geography and isolated populations may develop differently because of chance mutations or sampling accidents. More usually, the distinctions between populations arise due to *different selection pressures* resulting from facing a slightly different environment.

[4] Systems of technology are complex systems as they consist of many parts, with potentially complex interactions between those parts.

> *'… naturally evolve to a critical state in which a minor event starts a chain reaction that can affect any number of elements in the system'*
> (Bak and Chen, 1991, p. 26) .

The theory was initially illustrated by its authors using an example of a sand pile. Assume a pile of sand is gradually constructed by dropping individual grains of sand at a controlled rate. Eventually the pile of sand will grow until the slope of the pile of sand reaches a critical angle (the *angle of repose*). If an additional grain of sand is added at this point, an avalanche of grains of sand will occur. The theory of SOC sought to determine the distribution of the size of these 'outcome events' in all systems which evolve to a critical state. The key finding was that the distribution of the size of outcome events followed a power law:

$$N(s) = s^{-\tau}$$

where s = size of an output event, $N(s)$ = the number of events of size s, and τ represents a parameter (>0).

The implication of this, if technological systems do exhibit SOC, is that the impact of a given invention is indeterminate *a priori*. It will depend on the state of the technological system, for example the nature of the pre-existing technological fragments, at the time the invention occurs. The theory of SOC also posits that

> '*Most of the changes* [in a system] *take place through catastrophic events rather than by following a smooth gradual path. The evolution to this* [critical] *state is established solely because of the dynamical interactions among individual elements of the system: the critical state is self-organized.*'
> (Bak, 1996, p. 1)

If technological systems do exhibit SOC, most major changes in a technology paradigm occur as a result of sudden radical inventions rather than from a gradualist process. However, the occurrence of these radical events are not special in themselves, an apparently minor invention can result in a major shift in a technology paradigm simply because the technology system was already poised in a critical state. This argument suggests that a technological system may exhibit metastable characteristics much of the time and then change unexpectedly. In summary, the key issue in SOC is that avalanches of technical change occur periodically according to a power law and the implications of an individual event [invention], may be

> '*… understood only from a holistic description of the properties of the entire pile rather than from a reductionist description of the individual grains* [inventions].' (Bak, 1996, p. 2)

Although it is still an open question as to whether technological systems exhibit SOC behaviour, the model does succeed in incorporating both a gradualist and punctuated-equilibrium perspective. It also highlights the danger of ex-post story-telling in attempting to rationalise the significance of a particular invention.

Kauffman (2000) suggested that technological invention may be an *autocatalytic system*. As the number of traded goods (including raw materials and intermediate goods) or services increases (to say N), the potential number of complements or substitutes increases at a rate of $\mathbf{O}(N^2)$ since each item may be a complement or substitute of any other object. Under this perspective, the *diversity* of goods and services is a major driver of technological invention as a greater diversity increases the number of new combinations that can be invented. The technology landscape is open rather than closed. Kauffman (2000) claims that the recombination process is governed by a '*grammar*' (set of rules) which determines which recombinations are deemed possible or useful. The concept of a grammar or mental representation in the minds of inventors underscores the significance of culture and path-dependencies in the process of invention.

Although the above suggestions from the complexity sciences are tentative at present, they do represent a counter-point to traditional perspectives on the nature of technological invention. In particular, they challenge the idea, that on a global basis, the trajectory of technological progress can be anticipated. Proponents of complexity perspectives comment that in complex adaptative systems (including technology), construction of models which would allow prediction is a non-viable objective, rather enhanced understanding of the processes underlying the adaptative system may be all that is possible (Bak, 1996).

2.3 Innovation as search

A common view and one which is adopted in this paper, is that technological invention can be conceptualised as a search process (March, 1991; Lobo and MacReady, 1999; Kauffman, Lobo and MacReady, 1998; Fleming and Sorenson, 2001). The Schumpeterian view of creative destruction explicitly considers that the search for profit opportunities drives a never-ending process of technological invention and innovation.

A search process requires both a *navigation strategy* and *a structure* to be searched (Brabazon and Matthews, 2002a). The structure is the representation space within which search occurs, and the navigation strategy determines from where the search process is started, how the search process moves around the search space[5] and finally, the stopping rule for the search process. The starting point may consist of a current design, the objective of the inventive process being to develop a novel product to attain a pre-determined functionality. The inventive process iterates until this object is attained or is deemed unfeasible.

The above description of a search process poses two broad questions:

- What is being searched by inventors?
- How do inventors search?

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[5] Implicit in the navigation strategy is the idea of the '*memory*' or history of the search. Given the results of the search so far, how should it proceed at the next step.

The first of these questions in addressed in the following paragraphs, the second is deferred until the next sub-section.

The landscape metaphor is employed and technological search is considered to occur on an appropriately defined landscape. This landscape is defined over technological 'fragments', with each dimension corresponding to variants of a technology fragment. For example, in the 'invention' of a new computer, one of the dimensions could consist of the possible choices of microprocessor available for inclusion in the new computer. If the invention process is concentrating on the creation of a new form of microprocessor, the relevant dimensions could consist of the various technological ideas / fragments underlying existing microprocessor designs. It is acknowledged that the landscape is open rather than closed (new discoveries are possible) however, even radical inventions often primarily impound existing components.

Under the definition of technological invention adopted in this paper, the invention process will generally be '*directed'* to satisfy a product specification. Therefore, the invention process bears similarities to the product design problem. It is distinguished from this on the grounds of relative uncertainty. Invention bears stronger comparison with for example, the new drug discovery process, where the chance of successful invention is relatively low, whereas product design is considered more similar to the development of a generic version of an off-patent drug. In this latter case, the underlying technology is well understood and chances of successful product design are high. In essence, invention takes place on a less certain landscape of possibilities than does product design.

2.4 Search Heuristics

A significant literature exists in operations research regarding search algorithms. A search algorithm is a strategy or plan to efficiently attempt to locate a global extrema of a mapping. Due to the bounded rationality (Simon, 1955) of inventors it is argued that the invention process is likely to consist of heuristic, as distinct from mathematical, search algorithms.

Inventors face an inherent tension between exploration and exploitation (March, 1991), the former (broadly speaking) attempting to generate radical, novel designs using as yet undiscovered components, the latter attempting to re-use existing components. Allocation of resources between the two is complicated as

> '*…returns from exploration are systematically less certain, more remote in time, and organizationally more distant from the locus of action*.'
> (March, 1991, p. 73).

Kauffman (2000) points out that the rate of technological exploration depends on the '*discount factor'* that an organisation applies to such projects. Apart from the uncertainty of payoff regarding investments in exploration activities, these activities have an opportunity cost, the lost benefits from refining and exploiting existing technology. Inventors' assessment of these risks and costs will be partly driven by past experience. The tension between exploration and exploitation in invention activities may result in the '*competency trap*' of Levinthal and March (1993), whereby inventors are resistant to employing recently discovered components (or from attempting to discover novel components) in their inventive efforts and persist with recombinative efforts utilising familiar, well-understood technologies. Hence, technology searches embed both a history and expectations, suggesting that they display path-dependencies. The results of past searches become natural starting points for initiating new searches (Stuart and Podolny, 1995).

Search heuristics adopted by inventors consist of a mix of:

- problem decomposition (Cooper, 2000),
- incremental trial and error (Helfat, 1994) and;
- reuse of proven components (imitation) (Birchenhall, Kastrinos and Metcalfe, 1997)

These heuristics incorporate beliefs about what is '*feasible or at least worth attempting*' (Nelson and Winter, 1977, p. 57) and are embedded in a technological paradigm. Given the costs and risks of exploration, it is argued that inventors will be predisposed to engage in directed, exploitation activities, attempting to create inventions from existing components. Schumpeter (1934) noted that entrepreneurs do not randomly sample the space of technological possibilities, rather (p.68):

> '*...development consists primarily of employing existing resources in a different way.* '

and known building blocks are recombined. Many inventions can be considered as resulting from recombinations of existing technological components in novel ways (architectural innovation) or the use of existing components in novel application domains (Levinthal, 1998; Kogut and Zander, 1992). The recombination of existing components to produce new products, is equivalent to taking '*jumps*' on the underlying technological landscape. These jumps may either be long or short (from the current or starting point of the search), the latter corresponding to local search. An example of local search would be the incremental addition of a novel component into a pre-existing product. As an example, this could arise if a newly invented microprocessor was substituted for an older one in a PC. Here, the bulk of the PC's design is unchanged by the introduction of the new component. The key point of this example is that *recombination can serve as a local search heuristic.* The utilisation of a recombination heuristic in the invention process can lead to *either* local search or radical search, depending on the *degree* of recombination applied.

In the next sub-section, drawing on the prior work of Olsson and Frey (2001), a formal model is proposed which although not attempting to incorporate all aspects of the invention process, usefully integrates a number of themes from the preceding sub-sections. The model provides a visual representation of a recombinative invention process, and extends this to provide intuition on the development and exhaustion of a technological paradigm. Under certain assumptions, the model suggests that recombination events corresponding to local search are optimal.

3.0 THE FORMAL MODEL

The model outlined in this section assumes that the primary search heuristic adopted by inventors is recombination. It is further assumed that inventions arise from binary recombination of technological components[6]. Inventions, both existing and as yet undiscovered, are considered to form a '*technology space*'[7]. In this space, inventions are separated by a '*technological distance*', some inventions may represent minor alterations to existing components, others may represent major changes. The concept of a technology space provides a framework for integrating both a recombinant and a 'leap of creativity' (trial and error) perspective on technological invention, as well as providing an appealing visual representation of these processes.

Three terms are initially defined (Olsson and Frey, 2001) and are illustrated in **Figure 2**:

- Technology space
- Technology set
- Technology opportunity set

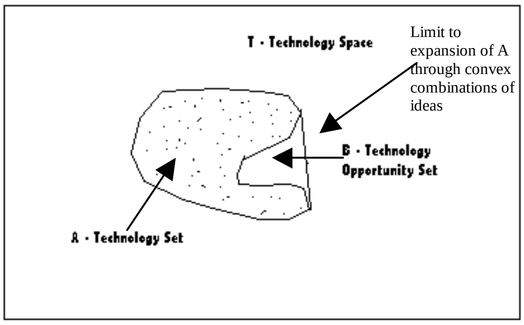

Figure 2: Technology Space and (opportunity) Set

The *technology set* is a subset of technology space. Technology space (***T***) is the set of all possible technological ideas for goods, in the past, present and future. This space may have many dimensions. The technology set $\boldsymbol{A_t}$ contains all the ideas which are held relevant at time *t*. Therefore it includes both current inventions and the older inventions on which these are based. In the analysis that follows, attention is restricted to binary pairings of technological ideas, however, the analysis could be extended to encompass the combination of multiple technological ideas.

The following assumptions are made:

1. $\boldsymbol{A_t} \subset \boldsymbol{T} \subset \mathbb{R}_+^k$, where $\boldsymbol{k}$ is the number of dimensions of $\boldsymbol{T}$
2. If $i_1, i_2 \in \mathbf{T} \subset \mathbb{R}_+^k$, then $d(i_1, i_2) \in \mathbb{R}_+$ is the *technological distance* between i_1 and i_2
3. Assume that $\exists$ a real number $\boldsymbol{M}$ and a point $i_1 \in \boldsymbol{T}$ such that $d(i_1, i_j) < \boldsymbol{M}$ for all $i_j \in \boldsymbol{A_t}$

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[6] This is adopted to simplify notational and graphical representation. If preferred, invention could be considered as a 'blending' of multiple technological fragments and the notation could be reworked for this case. The results are qualitatively unchanged.

[7] The nature of technology fragments and the corresponding definition of the technology space are discussed in Section 4. For now, it is noted that they can be represented using a binary string .

4. Assume that in normal technical advance, all new ideas i_n are the outcome of convex combinations of existing ideas $i_j, i_k \in \boldsymbol{A_t}$. Therefore, $i_n = \lambda_n i_j + (1-\lambda) i_k$ where $\lambda_n \in (0,1)$.

These assumptions imply the following characteristics of the technology set and the technology opportunity set.

1. The *technology set* $\boldsymbol{A_t}$ is infinite, bounded, closed and connected at all $\boldsymbol{t}$.

   The number of possible ideas in the set is infinite, however the set is bounded as there is a limit to the distance between any two ideas. The set is closed and therefore contains its boundary points. These points constitute the *technological frontier* at time $\boldsymbol{t}$.

2. The *technological opportunity* set, $\boldsymbol{B_t}$ is the smallest set such that $\boldsymbol{A_t} \cup \boldsymbol{B_t}$ is convex.

   $\boldsymbol{A_t} \cup \boldsymbol{B_t} = \boldsymbol{P_t}$, where $\boldsymbol{P_t}$ constitutes the *technological paradigm*.

In **Figure 2**, $\boldsymbol{k} = 2$ for ease of exposition. The technological opportunity set represents the unique area into which entrepreneurs might expand technical knowledge. In this model, '*normal science*' is considered as an incremental increase in knowledge in an attempt eliminate non-convexities in $\boldsymbol{P_t}$. This idea is consistent with the proposition that inventors' efforts are influenced by '*general purpose technologies* ' (Helpman, 1998) which anchor inventive efforts in various industries. If we further assume that inventors are more likely to engage in recombining technologically close ideas, perhaps due to bounded rationality, then expansions in $\boldsymbol{A_t}$ are most likely through convex combinations of ideas which are close to one another on the non-convex part of the technology frontier. Although it is possible to combine interior ideas from $\boldsymbol{A_t}$ to reach a point in $\boldsymbol{B_t}$, the cost of recombinations which are a large distance apart (assuming these costs increase with distance) may discriminate against such efforts. Over time, as $\boldsymbol{A_t}$ expands there is a resulting decrease in the remaining area of $\boldsymbol{B_t}$. A technological paradigm shift occurs if $\boldsymbol{P_t} \neq \boldsymbol{P_{t+1}}$. In this case, non-convexities are reintroduced and 'normal science' (local recombinations) recommences. As $\boldsymbol{B_t}$ is exhausted, opportunities for generating returns in the inventive process as a result of continuing to exploit existing knowledge, decline and the opportunity cost of exploring unknown regions of technology space is reduced.

The model as developed provides a mental picture of the role of recombination in the inventive process. However, no formal insight is provided on the important question of what forms of recombination offer most potential for inventors. Assuming inventors are driven by a profit-seeking motive, they will focus their inventive efforts based on expectations of returns. To incorporate these into the model, assumptions on the revenue and cost functions faced by inventor are required. Initially, the cost function is considered.

Assume the cost of creating a new invention, i_n by combining two existing ideas $i_l, i_m \in \boldsymbol{A_t}$ is a function of their distance apart (d). The rationale behind this assumption is that the combination of two disparate ideas is likely to require a greater degree of expertise and difficulty, than incremental invention. Define the cost function as,

$\boldsymbol{C}(i_n) = \delta\, [d(i_i, i_n) \,.\, d(i_n, i_m)]$ where $\delta > 0$ is a scaling parameter.

As above, inventions are linear combinations of existing inventions, $d(i_i, i_m) = d(i_i, i_n) + d(i_n, i_m)$, where the size of $d(i_i, i_n)$ and $d(i_n, i_m)$ depends on $\lambda_n \in (0,1)$. Since, $d(i_i, i_m) = d(i_i, i_n) + d(i_n, i_m)$, an increase in $d(i_i, i_m)$ is associated with an increase in $d(i_i, i_n) \,.\, d(i_n, i_m)$ and hence also in the costs of combination.

Substituting $d(i_i, i_n) = d(i_i, i_m) - d(i_n, i_m)$ into the cost function gives,
$\boldsymbol{C}(i_n) = \delta\, [d(i_i, i_m) - d(i_n, i_m))] \,.\, d(i_n, i_m)$. Holding $d(i_i, i_m)$ fixed but allowing $d(i_n, i_m)$ to vary, the first order condition for a maximum is :

$$\frac{\partial C(.)}{\partial d(i_n, i_m)} = \delta\, [(d(i_i, i_m) - 2d(i_n, i_m)^*)] = 0$$

and the second order condition is :

$$\frac{\partial^2 C(.)}{\partial d(i_n, i_m)^2} = -2\delta < 0 \quad \text{(always true)}$$

Rearranging terms in the first-order condition, gives $d(i_n, i_m)^* = d(i_i, i_m)/2$, therefore, the maximum cost of recombination arises when the new idea is located halfway between the recombined existing ideas. Intuitively, this suggests that recombinations of ideas which are dominated by one of the recombined ideas are less costly than equally weighted recombinations. This result supports an argument for the prevalence of local search[8]. The result provides intuition which suggests that the costs of novel recombinations are a function *both* of the distance between the ideas combined and the degree of linear combination between them.

The higher costs of 'half-way' combinations could be outweighed by expected higher revenues if these combinations tended to produce highly profitable inventions. Unlike the cost function, there is no compelling reason to assume a monotonic relationship between revenues accruing to recombination and the distance between recombined technologies. If it is assumed that revenues are an non-increasing function of $d\,(i_i, i_m)$, it is implied that rational entrepreneurs will combine ideas which are technologically close. Although this reasonably apparent from the above discussion on costs, a short formal proof is provided.

The inventor faces the following problem

$$\max_{d\,(i_i,\, i_m)>0} \pi = \boldsymbol{R} - \delta\, [d(i_i, i_m) - d(i_n, i_m)] \,.\, d(i_n, i_m),$$ where π is profit and $\boldsymbol{R}$ is revenue

The first-order condition is $\dfrac{\delta\pi}{\delta d(i_i, i_m)} = -\,\delta\, d(i_n, i_m) < 0$, therefore an inventor should optimally try to minimise the distance between the originating ideas. This implies that

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[8] Of course, the result is dependent on the form of the cost function.

inventive efforts should be based on existing ideas which are in close proximity to each other[9].

The model as developed above provides a useful picture of the inventive process and is capable of encompassing several key ideas from the invention / innovation literature, namely

- recombination
- periods of gradual inventive progress (normal science) punctuated by paradigmic shifts
- an argument for the prevalence of local search.

In common with most formal models, the model does not attempt to incorporate all factors which could be relevant. Leaving aside specific assumptions within the model with which issue could be taken, two particular limitations are highlighted. In concentrating on the effects of recombination, the model omits consideration of either radical or incremental 'trial and error' (non-recombination) invention. The latter could lead to a 'blurring' of the boundaries of $\boldsymbol{A_t}$, the former to the discovery of a radical invention outside the current technology set or technology opportunity set. Therefore it is more appropriate to consider that the model attempts to explain what occurs in the 'normal science' period rather than providing insight into the process of paradigm shifts in technology. Despite this, it should be noted that substantial 'inventive' activity occurs within the realm of normal science. The fact that an invention arises from a recombination event does not imply that it cannot have major impact.

The second limitation revolves around the '*sampling*' nature of the invention process. Only a small fraction of the possible number of recombinations are ever constructed. Whether a sampling process leads to a good understanding (and clear definition) of the current technology set, depends on the nature of the underlying technology landscape. The Kauffman NK model, discussed in section 4 provides a useful model for considering the 'ruggedness' or topology of this landscape. The more rugged the technology landscape, the less information is gleaned from previous recombinations and the poorer the understanding that inventors' have of the existing technology set.

4.0 NK MODEL

The origins of the NK model lie in studies of adaptive evolution (Kauffman and Levin, 1987; Kauffman 1993) but application of the model has expanded greatly beyond this domain to include energy landscapes (Weinberger, 1991), technological change (Kauffman, Lobo and Macready, 1998), organisation design (Levinthal, 1997) and product innovation (Frenken, 2001). In essence, the NK model attempts to understand the properties of items of interconnected components. Invention of all but the most trivial products, consists of the construction of a system of multiple, connected components.

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[9] It can be considered that the discovery of a radically new technology may initially create a new technology 'island' (set). Over time, the new 'island' will merge with the pre-existing technology set. This integration could take some time. A parallel can be drawn with Levinthal's (1998) speciation event, whereby several technology island could exist at any time, a speciation event occurring when an 'island' is first 'invaded' by a technology from another island.

4.1 Description of NK model

The NK model considers the behavior of items which consist of a vector of **N** components, each of which in turn are interconnected to **K** other of the **N** components (**K< N**). Each of the **N** components can assume a number of states or 'versions'. If the number of versions (states) for each component is denoted by $\mathbf{S_n}$, the N-dimensional space consists of $\prod_{n=1}^{N} S_n$ possibilities. Without loss of generality (Kauffman, 1993), the vector of N components can be considered as a binary string of 0s and 1s and therefore, there are a total of 2^N distinct versions of the item under consideration (possible states of the system). In the context of technological invention, each binary string represents the design specification underlying a physical invention.

The key concept underlying the NK model is that the value, functionality or *fitness* of a binary string (or design) depends both on the state of each individual component of that string, and the states of the components to which they in turn are connected. For example, the contribution of a Pentium 4 processor to an invention depends on the nature of the invention. It may contribute considerable utility of the invention is a piece of consumer technology, but little or no utility if the invention is a paper punch. The parameter **K**, determines the degree of interconnectedness of each of the **N** components and can vary in value from 0 to **N**-1. In the limiting case where **K**=0, the contributions of each of the **N** components to the overall fitness value of the system are independent. When **K**=**N**-1, the fitness contribution of any of the **N** components depends both on its state and the simultaneous states of all the other **N**-1 components.

4.2 Example of NK model

Let each component be represented by a binary variable (0,1). Thus possible configurations of the system when **N**=3 include 0 0 0, 1 0 1 and 1 0 0. In total, eight such configurations (2^3) exist. The calculation of the fitness value for each configuration depends on the value of **K**, which is assumed to be a constant value for all the components. If **K** = 0 each component of the binary string contributes independently to the overall fitness of the binary string. Kauffman (1993) models the fitness contribution of each of the individual components by drawing a random number from the uniform distribution (0,1)[10]. The overall fitness of the string is calculated as the average of the fitness values of each of the individual components. Therefore, if the individual fitness values are ***f1***,***f2***, and ***f3***, the overall fitness of the string is given by:

$$\boldsymbol{F} \quad = \quad \frac{\sum_{\boldsymbol{i}=1}^{\boldsymbol{N}} \boldsymbol{fi}}{\boldsymbol{N}}$$

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[10] Weinberger (1991) shows that the qualitative features of these landscapes can be generalised to cases where fitness values have a Gaussian distribution. The Central Limit Theorem shows that this will be approximated once the fitness values are determined by a large number of relatively independent factors of similar strength. There are good reasons to suppose that many components in product systems will be independent (Simon, 1996) as inventors will usually implement modular architectures (Brabazon and Matthews, 2002b).

In the case where **N**=3, the configuration possibilities can be represented as the coordinates of a cube. In higher dimensions, a hyper-cube is described. **Figure 3** provides an example of a landscape where **N**=3 and **K**=0.

String	*f1*	*f2*	*f2*	*F*
000	.4	.7	.1	.40
001	.4	.7	.3	.47
010	.4	.6	.1	.37
011	.4	.6	.3	.43
100	.9	.7	.1	.57
101	.9	.7	.3	.63
110	.9	.6	.1	.53
111	.9	.6	.3	.60

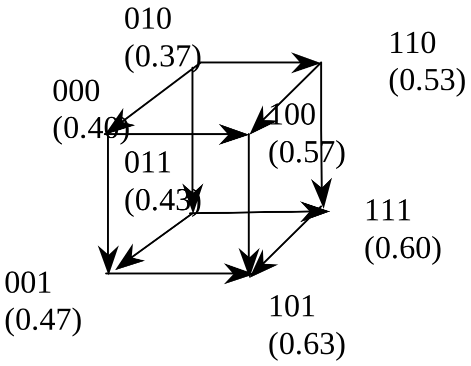

Figure 3: N=3; K=0

When **K**=0 and the contribution of each individual component is independent, the fitness values change smoothly between adjacent vertices as only one of the three terms contributing to overall fitness changes. When **K**>0, the fitness contribution of individual components becomes linked to the fitness of other components. For example, if **K**=2, the fitness assigned to an individual component depends not just on its own state but also on the state of the other two components. In an organisational setting, N could represent a vector of strategic parameters (or decisions) that managers can alter. The effect of altering one of these depends on the state (value) of other related parameters. Therefore, the fitness value of (say) a 0 in the first bit depends on whether it is followed by 00, 01, 10 or 11. In Kauffman's model, the fitness values of 000, 001, 010 and 011 are assigned by randomly drawing from the **U**(0,1) distribution. The implicit assumption is that the epistatic relationship between the components is unknown and is modelled as draws of a random number. **Figure 4** provides an example of a landscape where **N**=3 and **K**=2.

String	*f1*	*f2*	*f2*	*F*
000	.3	.6	.8	.57
001	.5	.3	.5	.46
010	.2	.7	.4	.43
011	.8	.6	.9	.77
100	.9	.6	.1	.53
101	.5	.3	.7	.50
110	.3	.1	.3	.23
111	.7	.9	.2	.60

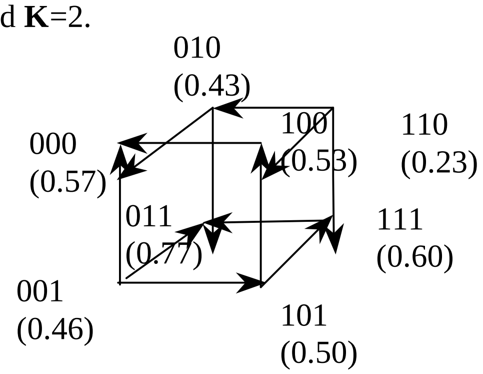

Figure 4: N=3; K=2

A key idea which emerges from the NK model, is that as **K** increases, the landscape becomes less smooth, more rugged and local search becomes less effective. Intuitively, the more rugged a landscape, the greater the number of local optima that exist.

In Kauffman's formulation of the model, the move or search operator is assumed to consist of bit-flips, whereby individual components of a binary string are switched from 0 to 1 or vice versa. Under this definition, local search consists of examining neighbouring strings (those which differ from the initial string by a single bit). The search heuristic is to alter the current binary string in a random position by changing one bit. If the new string has higher fitness it is accepted by the inventor and search recommences from the new string. This corresponds to a 'hill-climbing' heuristic, in that it continuously seeks to improve the fitness of the string and only stops when no bit-flip in the current string can produce an improvement. This point represents a local optima on the fitness landscape in that it is higher than all its one-bit change neighbours. An extensive literature exists regarding the properties of the fitness landscape under this formulation of the search heuristic. As the value of **K** increases, the number of local optima on the fitness landscape increases to $\mathbf{O}(2^N / N)$ and the average walk to the nearest local optima can be shown to be $\mathbf{O}(\ln N)$ steps (Kauffman and Levin, 1987). However, only a small portion of the total number of local optima are accessible from any given bitstring (Weinberger, 1991). As **K** increases, and the system becomes more tightly coupled (Glassman, 1973), the landscape becomes increasingly 'rugged' (Macken and Perelson, 1989). Increasing the value of **K** also reduces the mean fitness of local optima so they fall closer to the mean fitness of the entire space (Kauffman and Levin, 1987).

In the above diagrams, it can be seen that under a hill-climbing search strategy in which an inventor changes a single bit and 'accepts' the first change that produces an increase in the design's fitness, there is a single optimum point in the case where **K**=0 which is accessible from any starting point. The basis of attraction of this peak is the entire configuration space. In the case where **K**=2, there are two peaks, each with their own basin of attraction, a local peak at 000 and a global peak at 111. When **K**>0, search becomes increasingly 'path dependent'. Intuitively, as **K** increases, a web of *conflicting constraints* emerges[11]. In attempting to enhance the performance of one component of the system, unforeseen negative consequences arise elsewhere. In essence, **K** represents a '*tuning*' parameter (Weinberger, 1991) and by varying the value of this parameter, a wide variety of landscapes can be described. If **K**=0, then similar technological designs (similar binary strings) will have similar fitness values. As **K** increases in value, the correlation between the fitness of similar technological designs will reduce.

4.3 Implications of the Basic NK Model

The basic NK model has several implications for the process of technological invention. As **N** increases over time, the number of possible combinations of components increases exponentially. Only a limited number of all the possible physical recombinations of components will be undertaken by inventors. Inventors attempt to select combinations which are likely to be worthwhile, based on experience and the outcome of prior inventive attempts. These prior attempts represent a sampling process from the convex technology set described by all possible recombinations. Unfortunately, as **N** and/or **K** increase, the technological landscape faced by the inventor will become more rugged. This implies that the ability of the inventor to assess the potential of new combinations of components, based on prior

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[11] As noted by Kauffman and Macready (1995), the design of many products is laden with conflicting constraints. Examples provided include airframes and computer chips (p. 32).

inventive trials will tend to decrease possibly leading to ‘islands of inventive activity’ within the technology set.

Earlier discussion of the nature of technological change has suggested that it may display punctuated-equilibrium characteristics. In this setting, the relative efficiency of exploitation and exploration inventive processes are likely to vary over time. The NK model provides insights which can help explain why this occurs. Assuming an inventor commences a technology search at a point of average fitness, a variety of far away technological positions on the landscape could have vastly improved fitness, hence radical recombinations may be attempted. As the fitness of the uncovered design improves, the efficiency of long-jump (major recombination) technological search will decrease relative to local (minor recombination) search. At each step, the average number of long-jump trials required to find a better technological position doubles (Kauffman, 1995, p. 195). This provides a number of critical insights into product and process innovation. Initially when a technological improvement is uncovered, product proliferation occurs, corresponding to long-jump search. After several iterations, the most promising technological variants are uncovered, and the emphasis turns to exploitation of existing technological variants. With the revelation of the fitness potential of each technology, technological convergence occurs. A related process occurs within firms when a new technology is introduced. As the technology is exploited following an adaptive walk, as each uphill step is taken, the number of additional steps required to be examined to continue to move upwards increases at an exponential rate. This explains the ‘typical’ (power-law) shape of learning curves (Lobo and Macready, 1999, p. 18).

4.4 Extending the model

Earlier sections of this paper advanced an argument that a large portion of ‘normal invention’ consists of a recombinative process. This can also be referred to an a *blending* process wherein two or more technologies are combined (Cooper, 2000). In the context of ‘real-world’ invention, the search heuristic of the basic NK model is unrealistic. Although individual bit-flips can be considered as resulting from either an incremental trial and error experiment or a minor recombinative event, restricting attention to single bit-flips is unduly limiting. A recombinative event could alter several bits. The NK model suggests that the probability of successful invention through recombination is likely to be low when

- **K** is high
- Recombination alters a significant number of bits

If **K** is high, the landscape is rugged and a ‘long jump’ on such a landscape corresponding to large-scale recombination will result in an unpredictable result. Thus, the NK model suggests that the result of recombination during invention is more likely to be predictable / foreseeable when minor recombinative events occur. As value of **K** falls, the ‘correlation length’ of the landscape increases. In correlated (smoother) landscapes, higher levels of recombination are feasible as their results are foreseeable. Given the strong tradition of arguing that most inventions stem from recombinative events, the above implies that either **K** is usually low relative to **N** or most recombinative events are small in size relative to the total scale of the design. A common method of designers / inventors to reduce the value of **K** is to adopt modular or decomposable design architectures (Brabazon and Matthews, 2002b). In cases when **K** is low, high payoff peaks on the technology landscape tend to cluster near one another. Hence, as K decreases, the landscape becomes statistically nonisotropic.

5.0 DISCUSSION

The search for novel inventions takes place on a vast landscape of possibilities. In an effort to constrain the range of possibilities considered, inventors employ search heuristics. This paper considers one of these heuristics, recombination and provides an exploration of some of the implications of inventors using a recombination search heuristic for the process of technological invention. In biological evolution, it is posited that recombination mechanisms are responsible for the majority of novel forms (Mayr, 2001). In a technological domain, recombination can create novelty either by transferring technological fragments from one application domain to another (speciation), or through creation of new architectures of components.

A model is developed to explore the implications of a recombinative search heuristic. It is demonstrated that, subject to the assumptions of the model, a recombinant process acts to create a convex space of inventive possibilities. Periods of 'normal science' are explained as the eliminations of non-convexities in a technological space, whereas paradigmic shifts serve to reintroduce them. The theory also provides an explanation for the prevalence of local search by inventors, in terms of seeking to minimise search costs. Finally, the nature of the landscape on which recombinant search takes place is considered, using Kauffman's NK model. This provides insight into the effectiveness of a sampling process of recombination for gaining understanding of the profit potential of untried combinations. As the landscape becomes more rugged, the ease with which an inventor can assess, ex-ante, the likely utility of a novel combination of components is reduced.

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