# AN EVOLUTIONARY APPROACH TO THE PROCESS OF TECHNOLOGY DIFFUSION AND STANDARDIZATION

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**Abstract**

The study described here aims to make a threefold contribution to the analysis of technology diffusion. First of all, it tries to offer a new approach to the study of the dynamic of innovation diffusion, not from the traditional perspective of the *rate* at which *one* new technology is fully adopted, but the *extent* of the diffusion of *several* technologies and the related phenomenon of standardization. Secondly, it aims to show a broadened and evolutionary view of the process of technology standardization, avoiding the habitual determinism of conventional models of technology diffusion and lock-in. Finally, it tries to identify and evaluate the relationships existing between the main characteristics of industries and the attributes of the technology standardization processes in them. To achieve these goals we have developed an agent based model (ABM), using distributed artificial intelligence (DAI) concepts drawn from the general methodology of social simulation.

**Keywords**

Technology diffusion; standardization; lock-in; evolutionary models; agent-based models

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## INTRODUCTION

Technology diffusion is a process whereby innovations, whether new products, new processes or new management techniques, propagate within and between economies (Stoneman, 1986). Although the evidence on technology diffusion is inconclusive, there is a broad consensus on two aspects of the process: (i) the rate at which the use or ownership of a technology propagates in an economy changes over time (Mansfield, 1961 and 1968); (ii) the diffusion of new technologies follows a predictable pattern over time, which may be represented graphically by an S-shaped curve (Griliches, 1957; Mansfield, 1961; Davies, 1979; Gort and Keppler, 1982). These demonstrated facts have led researchers looking at technology diffusion to focus mainly on two interrelated questions: firstly, why do some innovations spread more rapidly than others? And, secondly, why do some companies adopt a given innovation more rapidly than others? The focus has therefore shifted onto trying to explain both the *rate* at which innovations are adopted and the *order* in which these innovations are adopted.

However, the literature on technology diffusion has devoted very little attention to another, equally interesting question: why do some innovations sometimes become ubiquitous and turn into *de facto* standards or dominant designs, whereas other innovations diffuse only partially or not at all? (Abrahamson and Rosenkopf, 1997). Moreover, as a result of those two former questions, most research into the factors influencing technology diffusion have focused on the characteristics of the *technologies* (epidemic models, Mansfield, 1961) such as risk, returns, complexity, intellectual property; and on the characteristics of the adopting *firms* (probit models, David, 1969), such as their size, capital vintage, expected returns from the new technology, factor productivity, search costs, and input prices. The few sectoral studies that exist, most of which are empirical, generally use average characteristics of companies belonging to a sector, given the difficulty of obtaining sectoral data. This means that they again turn into an examination of how firms' characteristics affect diffusion (Blackman, 1999). Moreover, their findings are inconclusive and at times even contradictory.

The study described here aims to make a threefold contribution to the analysis of technology diffusion. First of all, it tries to offer a new approach to the study of the dynamic of innovation diffusion, not from the traditional perspective of the *rate* at which *one* new technology is fully adopted, but the *extent* of the diffusion of *several* technologies and the related phenomenon of standardization. Secondly, it aims to show a broadened and evolutionary[1] view of the process of technology standardization,

[1] The main differences between the conventional or neoclassical approach to the analysis of technological change and the evolutionary approach adopted here basically arises from the objections of evolutionary economists to the way in which the (aggregate) production function is used by neoclassical economists and their apparent inability to explain the *processes* of technological innovation (Nelson and Winter, 1974, 1977 and 1982; Dosi, 1982; Dosi *et al*., 1988). Thus, while the neoclassical approach portrays technological change as a simple change in the information available on the relationship between the economy's *inputs* and *outputs* (Stoneman, 1983; Gomulka, 1990), the evolutionary approach considers technological change to be the result of a self-referential process of evolution influenced by the prevailing economic, social and political institutions. According to this approach, technological development should be understood as a process of evolution in which alternative technologies compete with one another and with the dominant technology, resulting in selection of winners and losers, with considerable uncertainty at the outset about who these winners will be (Nelson and Winter, 1982). Given that uncertainty is intrinsic to the process of technological change, the assumption of rational maximizing behaviour is

avoiding the habitual determinism of conventional models of technology diffusion and lock-in. Finally, it tries to identify and evaluate the relationships existing between the main characteristics of industries and the attributes of the technology standardization processes in them. To achieve these goals we have developed an agent based model[2] (ABM), using distributed artificial intelligence (DAI) concepts drawn from the general methodology of social simulation.

## I. TECHNOLOGY DIFFUSION AND INCREASING RETURNS TO ADOPTION

To construct our model we expanded the scope of the so-called "informational cascade" models (Bannerjee, 1992; De Vany and Walls, 1996; Bikhchandani et al., 1992 and 1998). First of all, it should be noted that new technologies appear on the market in a specific variety of forms, which, when they are sold directly to firms, may be interpreted as process innovations. Adopting a technology implies an initial choice of one of its multiple variants. When a number of "early adopters" decide to try out a variant of the technology instead of the established version, and they find it to be superior, the so-called "band-wagon" effect can take place, whereby later adopters follow the early adopters' decision, without having made the same investment in learning from experience. The "informational cascades" are defined as situations in which it is optimal for an individual, having observed the actions of those going before, to follow the behaviour of the preceding individual without considering his own information. The concept is similar to that of *replicator dynamics* (Schuster and Sigmund, 1983), a pattern which repeats itself in numerous evolutionary phenomena. Network externalities and other *increasing returns to adoption* reinforce this effect.

Within the field of evolutionary theories of technological change, in recent years growing number of authors have focused attention on the increasing returns to adoption –through positive feedback– on the dynamic of technology diffusion, and in particular on the phenomenon of technology standardization that often derives from it. One outstanding reference in the literature is Arthur (1989, 1990, 1994). According to Arthur, most of those parts of the economy based on physical resources (agriculture, mining, etc.) are subject to diminishing returns. On the other hand, the parts of the economy that are knowledge based (e.g. technology) are broadly subject to increasing returns. These require major investments in research, development and tools, but once sales begin, production can be increased relatively cheaply. As additional units are produced, the unit costs continue to fall and profits increase. Moreover, as greater production experience is acquired, producers learn how to make additional units more cheaply (learning by doing) (Arrow, 1962). Greater experience is also acquired in their use, and users' productivity increases (learning by using) (Sheshinsky, 1967). Positive externalities occur because the physical and informational networks are more valuable to users as they grow in size (Katz and Shapiro, 1985 and 1986; Farrell and Saloner, 1986a and b; Economides, 1996). As the number of people adopting a given technology

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replaced by a search for profit "in the dark" (heuristic search routines); as a result, there is no single welfare maximizing equilibrium, but rather a plurality of possible equilibria: historical accidents thus determine which equilibrium is reached or approached at any given time; the structure, including the institutions, is often made explicit in evolutionary models, so that its place in the process of technological change can be studied (Lipsey and Carlaw, 1998).

[2] Other common names for this discipline include: *Agent-Based Simulation*, *Agent-Based Computational Economics* (ACE) o *Multi-Agent Systems* (MAS).

grows, so the uncertainty is reduced and both the users and producers perceive reduced risks in its adoption. Their confidence in the quality and performance of the technology and perception of its likelihood of continuing to be available in the future therefore increases (Arthur, 1991). At the same time, the increase in the number of users reduces information search costs (Blackman, 1999). Thus, as an alternative technology gains market share, potential users have an increasingly powerful incentive to adopt that alternative, provided they are able to exchange information with those users who already have the technology. Moreover, a technology that improves more quickly or is adopted by more agents has improved chances of survival (*selectional advantage*). For this reason it is possible to say that "competition consumes its own fuel" (Metcalfe, 1994: 938), thereby reducing technological diversity. In terms of technological alternatives, "(...) technology is not chosen because it is efficient, but becomes efficient because it has been chosen" (Rip and Kemp, 1998: 353). According to Foster (1986: 96), once again an S-shaped curve shows precisely how the performance of a technology improves relative to the effort put into its development. In practice, a large part of this development is the result of economies of learning, which in turn depend on the degree of implementation and users' experience (Figure 1).

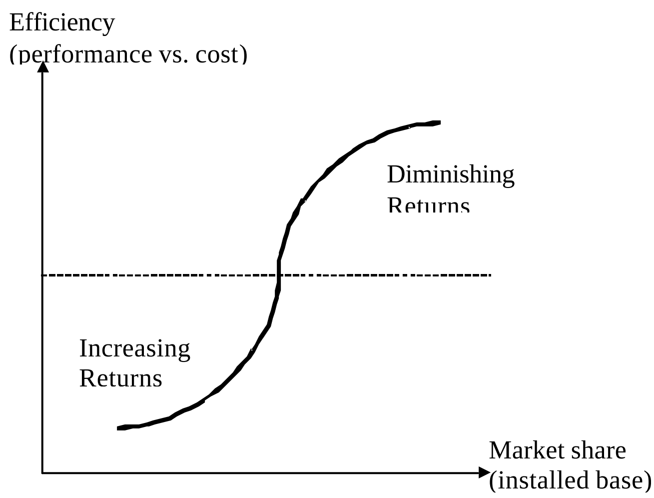


Fig. 1. Change in the performance of a technology with its market penetration (adapted from Unruh, 2000)

Returns are not constant with the growth in the adoption of the technology. This fact derives to a large extent from the increasing returns that certain technologies show during their development and commercialization (diffusion) phases and which can fortuitously accelerate their rate of improvement compared with competing alternatives. After a point of inflection, the possible improvements in performance are progressively smaller, and eventually reach a limit at which there is no further improvement even if new users are added (Moreau, 1999: 9; Laffond et al., 1999; Loch and Huberman, 1999: 12). Conventional economics focus on the top part of the curve (i.e. they consider that what is important is the return at the long-term equilibrium). When there are increasing returns to adoption the same distribution of technologies and user preferences can lead to different structures of results, depending on the way in which things start (*first mover advantage*) (Economides, 1996: 26). Early superiority, however, is no guarantee of long-term suitability (David, 1989; Cowan, 1990; Nelson, 1994). Thus we see that apparently inferior designs can be locked into the production system in a path-dependent process in which circumstantial events can decide the winning alternative

(David, 1985, 1997). Thus, one characteristic of the products or systems subject to increasing returns is that the way in which events unfold can be critical. Whereas other markets may be explained by current supply and demand, it is not possible to fully understand markets subject to positive feedback without knowing the historical pattern of technology adoption (Jaffe *et al*., 2000: 42; Economides, 1996: 26).

## II. STANDARDIZATION AND TECHNOLOGY LOCK-IN

According to Anderson and Tushman (1990), all areas of industry advance through a series of technology cycles. Each of these cycles begins with a technological discontinuity, triggered by the emergence of a breakthrough innovation, which significantly advances –by more than an order of magnitude– the state of the art characterizing a given industry. In terms of Foster's (1986) curves, this discontinuity could be represented as a "jump" between two curves (Figure 2).

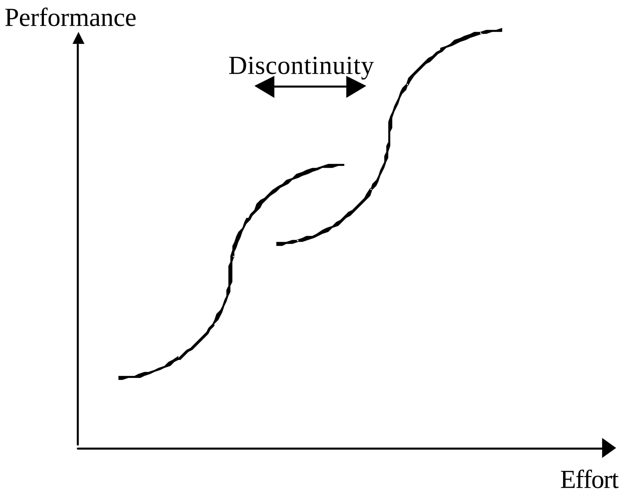


Fig. 2. Technological discontinuity
(adapted from Foster, 1986)

The concepts of "dominant design" and "standard" are frequently used interchangeably in the literature (Afuah, 1998; Schilling, 1998), although the notion of dominant design is broader and to some extent subsumes that of a standard (Suárez and Utterback, 1995: 417). A standard is understood to refer to a set of technical specifications to which the producer adheres, whether tacitly or as a result of a formal agreement (David, 1987). The process by which a dominant design or standard emerges is often considered a "black box", in that a wide spectrum of factors which are difficult to identify and measure can interact (Lee et al., 1995; Suárez and Utterback, 1995). This is precisely one of the questions to which this investigation aims to point to an answer.

It is generally accepted that complex technologies often show increasing returns to adoption (Schilling, 1998: 269). Under these conditions the system has a multiplicity of stable attractors or equilibria which, expressed in terms of market share, can be interpreted as spontaneous standards. These are also referred to as de facto or unsponsored standards (David and Greenstein, 1990). Typically, these are situations in which none of the agents has a proprietary interest in any of the main standards and no one firm is big enough to take into account the way in which its price decisions and technology choices could influence the actions of other sellers or users (op. cit.: 5). In short, spontaneous standards emerge as a result of internal market processes and not as the result of coordinated action by market participants. Early superiority, however, is no guarantee of long-term suitability (David, 1989; Cowan, 1990; Nelson, 1994a). Thus, given increasing returns, apparently inferior designs can be locked into the production system indefinitely in a historically-dependent process in which circumstantial events determine the winning alternative (David, 1985, 1997). It should be highlighted that the analysis of technological diffusion given in the literature on the phenomenon of technological lock-in has devoted very little attention to issues relating to the existence of previous alternatives or the conditions under which new technologies are able to displace old ones in a technological succession (Windrum and Birchenhall, 2000). In addition to Arthur (1989, 1990, 1994), many other authors have portrayed the technology selection process as an “all or nothing” story (Abrahamson and Rosenkopf, 1997). This is a general shortcoming of technology diffusion and standardization models which has repeatedly been highlighted in various studies over the last decade (Schilling, 2002: 395; Jaffe et al., 2000: 41; Windrum and Birchenhall, 1998: 112; David, 1997: 36; Nelson, 1994b; David and Greenstein, 1990: 8). It seems clear that, rather than the deterministic view of conventional models of technology lock-in, it might be worth having an expanded formal view of the process of technology diffusion and standardization which takes into account the possibility of a technological succession[3], understood as a series of replacements of old technologies by new technologies performing the same basic function (Grübler, 1990, 1991).

## III. THE MODEL

In the last few years simulation has become a popular means of discovering and exploring complex natural and social systems (Hannerman and Patrick, 1997). The recognition that social and economic phenomena frequently exhibit characteristics typical of complex systems –significant non-linearity among them– is a challenge to traditional research methods (Holland, 1998; Epstein and Axtell, 1996; Latané, 1996; Gilbert, 1995). Thus, simulation has been put forward as a new way of conducting research, a “third scientific discipline” (Ilgen and Hulin, 2000; Axelrod, 1997) that complements and is built on the traditional methods of induction and deduction. An important branch of simulation in the social sciences is agent based modelling (ABM), which is a form of modelling characterized by a number of autonomous agents which interact with one another and with their environment, with little or no central coordination (Conte et al., 1997; Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999; Weiss, 1999). Thus, the emergent properties of an ABM (i.e. the system’s macro-behaviour) are the results of bottom-up processes (arising from micro-level interactions between agents in the system) rather than of top-down processes. According to Wooldridge and Jennins (1995), in an ABM the agents are computational processes that are characterized by: i. their autonomy, in that they control their own actions; ii. social

[3] As will be seen below, our methodological approach to the problem being examined does not follow the path set by the few formal mathematical models that have attempted to elucidate the process whereby a technology is replaced by multiple alternatives (Peterka and Fleck, 1978; Marchetti and Nakicenovic, 1979) and, obviously, it also departs from binary models of technology replacement (Fisher and Pry, 1971). For this reason, in order to ensure a clearer and more direct exposition of our approach, we have not explained it at length. For more information on these models see, for example, Kwasnicky (1999).

abilities, i.e. the agents interact with one another by means of some kind of "language"; iii. reactivity, in that the agents can perceive their environment and respond to it; and iv. proactivity, in that they are able to carry out actions in order to achieve an objective. Clearly, to a large extent, agents in the business world exhibit these characteristics, a fact making ABM seem an appropriate methodology for studying emergent phenomena in markets. It should be highlighted that although ABM uses simulation its goal is not necessarily to represent a specific empirical application precisely, but rather to give us a more detailed understanding of the fundamental processes that may emerge in various applications. If this is the aim, what is important is the simplicity of the assumptions and not a detailed representation of a particular reality (Axelrod, 1997).

Building on the ABM research methodology, this section describes the model put forward to achieve the aims and compare the hypotheses of the investigation. Its calibration, verification and validation are also discussed.

### III.a ASSUMPTIONS OF THE MODEL

We assume an indefinite time horizon of $t$ periods in which time evolves discretely ($t \in \mathbb{N}$) and the dynamic is asynchronous. We assume a single good or service $X$, which may be produced using multiple alternative technologies $T_j\left(j=1,...,J_t,...,J\right)$, the characteristics of which are defined below. In each period t the free entry of one or more new individual producers $P_i\left(i=1,...,I_t,...,I\right)$[4] of $X$ takes place in a Poisson-type[5] random process with an average rate of appearance of new producers in a given period $\lambda_P > 0$, which for simplicity we assume to be constant over time. Thus the probability that $I_t$ new producers emerge in the period $t$ will be given by the probability function

$$f\left(I_t\right) = \frac{\left(e^{-\lambda_P} \cdot \lambda_P^{I_t}\right)}{I_t!}, \quad I_t = 1,2,\ldots I \qquad [1]$$

Each $P_i$ has an intrinsic survival parameter $s_i$ associated with it ($>0$). For simplicity this parameter is assumed to remain constant over time. In this simulation it is distributed independently at random between the different $P_i$ in a way that follows a normal distribution $N\left(\bar{s},\sigma_s\right)$. Thus, in each $t$ there is also the *free exit* of producers whose survival period has expired, with the rest remaining in the following period as old producers.

[4] Assuming a finite number of agents in the industry responds to one of the criticisms of Arthur's model, such as that raised by Dalle (1995) who questions the validity of "(...) assuming the existence of an infinite number of agents, as unanimity is not found except at the limit, making the time and therefore the number of agents tend to infinity. It seems to us that economic systems are constructed rather of a finite number of agents, who comprise a network and make use of local channels of information to enable them to make their decisions."

[5] The assumption of a Poisson distribution is realistic and is well established in the literature for situations in which numerous successive events (in this case, the entry of firms in the sector) have independent sources (Mayer and Chappell, 1992: 772; Loch and Hubberman, 1999: 6)

We assume that in each period $t$ one or more new alternative technologies appear on the market $T_j\left(j=1,...,J_t,...,J\right)$ in a way that cannot be anticipated by the agents producing the good $X$. These process innovations are provided by multiple technology suppliers[6], who act motivated by the pursuit of a patent which grants them a certain degree of monopoly power, albeit temporarily. We will suppose that these technologies arise following a Poisson-type[7] random process, with $l_T > 0$ constant over time[8].

$$f\left(J_t\right)=\frac{\left(e^{-l_T}\cdot l_T^{J_t}\right)}{J_t!},\quad J_t=1,2,\dots J \qquad [2]$$

It is assumed that any technology $T_j$ which has not been adopted at any time $t$ by at least $P_T\left(>0\right)$ producers –in accordance with the mechanisms described below– after $t_T\left(>0\right)$ periods have passed, is considered to have been "rejected" by the productive system and as of that point in time is no longer available.[9] We also assume that each $T_j$ can be characterized according to a set of criteria or characteristics $C_k^j$ which allow their performance[10] to be measured from $K$ different dimensions. Following Rogers (1995)[11], we propose the following technology characterization, although the number of criteria and their definition does not affect the main results of this model, the multi-dimensionality of the evaluation being the only genuinely important assumption[12]:

[6] According to Kemp (1997: 221) process innovations are generally developed by specialist suppliers, research institutions other than the producer firms, whereas product innovations are usually developed by the firms themselves. The model presented here deals with the diffusion of the first of these types of innovation: new technologies which substantially modify production processes.

[7] As done, for example, by Silveberg and Lehnert (1993), (1994).

[8] In this way the model overcomes another of the habitual criticisms of Arthur's model: "(...) a somewhat unconvincing hypothesis is usually adopted in technology competition models. In Arthur's model, for example, competing technologies appear simultaneously in a virgin market. It would seem more realistic to consider a new technology entering a market dominated by one or more well-established technologies" (Moreau, 1999: 8).

[9] "Those technologies that are not pre-selected or fail to slot into the system (...) are destined to fail and will not survive" (Arentsen et al., 1999: 9). This assumption could easily be relaxed if we accept that the new technologies that emerge in each period are "improved versions" of technologies which have been rejected by the market. This could give rise to the introduction into the model of the issue of learning by doing and learning by using in R&D (Jaffe et al., 2000: 44) and the "quality ladders" models (Sala-i-Martin, 1994: 113).

[10] According to David and Greenstein (1990: 30), performance-oriented specifications are generally preferable to design-oriented specifications, especially in the development of anticipatory standards.

[11] Following the main reference in the literature on this topic, Rogers (1995: 206), the *attributes* of an innovation *perceived* by its potential users explain to a large extent the rate of adoption of that innovation. According to this author, between 49 and 87 per cent of the variation in the adoption rate is explained by just five attributes: the *relative advantage* is the extent to which an innovation is perceived as being better than the idea that preceded it (the perception of the relative advantage of an innovation is positively related to its adoption rate); the *compatibility* is the extent to which an innovation is perceived as being consistent with existing values, past experience and the needs of potential adopters (this perception is positively related to the rate of adoption); the *complexity* is the extent to which an innovation is perceived as being relatively difficult to understand and use (this perception is negatively related to the adoption rate); the *trialability* is the extent to which an innovation can be tried on a limited basis (a perception that is positively related to the adoption rate); the *observability* is the extent to which the results of an innovation are visible to others (positively related to the adoption rate). With regard to the *sustainability*, see section 6 of this paper.

[12] The traditional approach to the decision to invest in a technology (adoption) has focused on the evaluation by the adopter of a single criterion, usually the expected return on investment. However, it is

$C_{Ak}$ : Adoptability criteria

$C_{A1}$ – Relative advantage

$C_{A2}$ – Compatibility

$C_{A3}$ – Complexity

$C_{A4}$ – Trialability

$C_{A5}$ – Observability

Thus, each $T_j$ can be characterized by a performance vector

$$\overrightarrow{D_j}\left( C_{A1}^j,\, C_{A2}^j,\, C_{A3}^j, C_{A4}^j, C_{A5}^j \right) \qquad [3]$$

with elements $C_k \in [0,1]$, where the values 0 and 1 represent the extremes of a "bad" or "good" evaluation of its performance, respectively, within this continuous range. In this way the proposed classification system allows a virtually unlimited number of alternative technologies $T_j$ for the production of the good $X$ to be characterized. Obviously, in reality this would be beyond the cognitive limits, and indeed the physical limits, of technological development. However, it demonstrates the flexibility of the proposed model compared with those[13] that centre their analysis on only two alternative technologies. In the simulation we also establish that, due to the presence of increasing returns to adoption (deriving from learning by doing and learning by using, network effects, economies of scale, increasing returns to information and technology interrelations) the real value of each $C_k$ (*actual performance)* for each $T_j$ evolves as a function of the degree of adoption by $P_i$ producers (*installed user base*). Where $C_{kt}^j$ is the value of the actual performance of $T_j$ in $C_k$ in $t$. As, in fact, the five individual selection criteria proposed are met, in the proposed range of values (range [0-bad,1-good]), we assume that $C_{Ikt}^j$ is an increasing function of the number of agents $P_i$ that adopt the technology $T_j$ in each $t$, $I_t^j = \sum_t P_i^j$ :

$$C_{Akt}^j = f\left(I_t^j\right) = \frac{\overline{C}_{Ak}^j}{1+\left(\left[\overline{C}_{Ak}^j - C_{Ak_0}^j\right] \Big/ C_{Ak_0}^j\right)\cdot e^{-r_j \cdot I_t^j}} \qquad [4]$$

This is an increasing logistic function[14] (Figure 3) with an upper asymptote at the maximum level of performance $\overline{C}_{Ak}^j$ or "frontier of improvement" which cannot be

widely accepted that the performance of a technology is a multi-dimensional construct (Anderson and Tushman, 1990: 627; Foray and Grübler, 1990; Suárez and Utterback, 1995: 418; Rogers, 1995: 206; Kemp, 1997: 88; Christensen, 1997; Windrum and Birchenhall, 1998: 114; Nelson, 2000: 70; Cantner and Hanusch, 2001: 229). Therefore, it would seem to be reasonable to asume that business people make their technology adoption decisions bearing in mind multiple dimensions or attributes of a technology, evaluating their (albeit imperfect) perceptions of them according to their (heterogeneous) preferences regarding each dimension or attribute.

[13] See, for example, Arthur (1983, 1988, 1989); Laffond et al. (1999); Farrell and Saloner (1986); Shy (1996); Cowan (1988).

[14] As argued in section 3, according to Foster (1986: 96), an S-shaped curve shows precisely how the performance of a technology improves in comparison with the effort used to develop it. In practice, much of this development is the

exceeded by each criterion of a technology, despite the accumulation of new adopters. $C^j_{Ak_0}$ represents the starting level of performance ($I^j_t = 0$) of $T_j$ in $C^j_{Ak}$. In the simulation, $\bar{C}^j_{Ak} > C^j_{Ak_0}$ is always fulfilled, both variables being distributed randomly and independently between the different technologies arising in the same period $t$ following a $N(0,1)$ within a range of possible values $[0,1]$. Also, an upper limit of $\widehat{C}^j_{Ak_0}$ is set for $C^j_{Ak_0}$, which should be closer to 0 than 1 in this continuous range.[15]

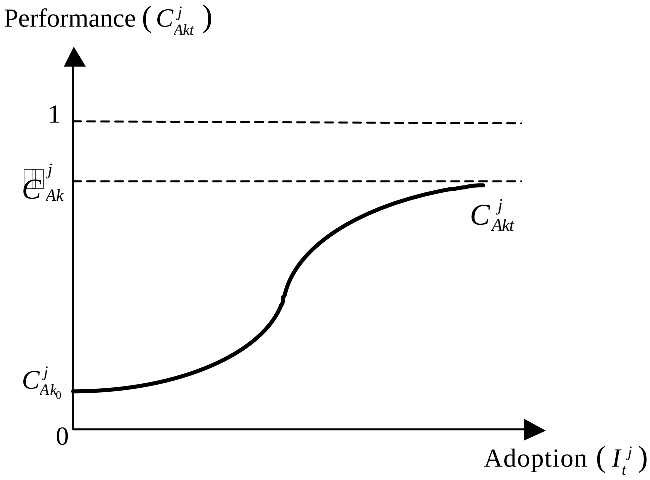


Fig. 3. Function showing the evolution of the performance of a technology as its adoption grows

The variable $r_j\,(>0)$ represents the rate at which $T_j$ improves as a result of the presence of increasing returns to adoption[16]. For simplicity, we will assume that the value of this rate of improvement $r_j$ is common to all the criteria of a given technology, although it is probable that in reality some technologies will improve more rapidly than others as the number of users increases. However, the model does incorporate the fact that the various alternative technologies will enjoy different degrees of increasing returns to

result of economies of learning, which in turn depend on the level of adoption and the experience of users. Many authors use similar functions: Loch and Huberman (1999: 12); Windrum and Birchenhall (2000: 12); Frenken and Verbart (1998).

[15] According to Kemp (1997: 273), "Numerous historical studies show that, at the moment of its introduction, new technologies were frequently underdeveloped in terms of their performance characteristics and offered scant advantages over existing technologies. They needed to be improved, both in terms of price and technical features, in order to spread more widely." According to Rosenberg and Frischtak (1983: 147), "new inventions are typically very primitive at the time of their emergence. Their performance is generally poor compared with the (alternative) technologies that exist and with their future performance."

[16] It should be highlighted that despite the fact that the increasing returns are different (deriving from learning by using and learning by doing, economies of scale, increasing returns to information and technological interrelations), they are usually handled together mathematically (Nelson, 1995: 74; David and Greenstein, 1990: 6; Cabral, 1987; Metcalfe, 1994: 937)

adoption. Thus, in the simulation $r_j(>0)$ [17] is distributed randomly and independently between the various different $T_j$ emerging in the same $t$ following an $N(\bar{r}, s_r)$.

We assume the information in this technology market to be imperfect, such that each potential adopter has a different *perceived performance* of each technology in terms of his own individual selection criteria[18]. $C_{Akt}^{ij}$ is the perceived value of the performance of technology $T_j$ by agent $P_i$ according to the criterion $C_{Ak}$ at time $t$. In the simulation we assume that $C_{Akt}^{ij}$ is distributed between the different agents, within the range of possible values $[0,1]$, according to a normal distribution[19] with its average at the actual value $C_{Akt}^{j}$ and a standard deviation of $s_{Akt}^{j}$: $C_{Akt}^{ij} \sim N(C_{Akt}^{j}, s_{Akt}^{j})$, where $s_{Akt}^{j}$ is a decreasing function of the number of agents adopting technology $T_j$ at a given moment $t$, $I_t^j = \sum_t P_i^j$ :

$$s_{Akt}^{j} = g(I_t^j) = \frac{1}{1 + c \cdot I_t^j} \qquad [5]$$

The parameter $c > 0$ represents the rate of communication between users. The function $g(I_t^j)$ incorporates in the model the fact that as the number of users increases, so the uncertainty and information search costs decrease, and agents' knowledge[20] of the actual performance of a technology, and their expectations of it increase[21]. This characterization of the process of diffusion of knowledge, which depends on the number

[17] Also, in the simulation, a value of $\bar{r} < 0$, for all $T_j$, would allow us to represent a situation characterized by decreasing returns to adoption, whereas with $\bar{r} = 0$ (and $s_r = 0$), for all $T_j$, we would be in a situation of constant returns to adoption.

[18] Rogers (1995: 206) argues that the *perceived attributes* of an innovation, as seen by its potential users, to a large extent explain the rate of adoption of the innovation. Frenken and Verbart (1998) point out that the return on the adoption of a technology probably depends on its *perceived* utility when a certain task is performed or a particular problem solved.

[19] Abrahamson and Rosenkopf (1993).

[20] We argued above that as the number of people adopting a given technology grows, so the uncertainty is reduced and both the users and producers perceive reduced risk. Their confidence in the quality and performance of the technology and perception of its likelihood of continuing to be available in the future therefore increases (Arthur, 1991). At the same time, the increase in the number of users reduces information search costs (Blackman, 1999).

[21] Before deciding whether or not to adopt a technology alternative, the potential users have limited and imperfect information about its actual performance. It is a generally accepted fact that agents' expectations regarding the diffusion of a technology affect their decision to acquire it or invest in it (Katz and Shapiro, 1985: 426; Farrell and Saloner, 1986: 941; David: and Greenstein, S., 1990: 7; Loch and Huberman, 1999; Mulder et al., 1999: 9). Despite this consensus, most models of technological change use the change in actual performance of the technologies in question as a fundamental axis of their dynamic (unless they consider it constant). The model proposed here takes an alternative and more realistic approach by focusing on the changing *perceptions* potential users have of the real performance of the technological alternatives. As happens in the real world, in the model these perceptions of a technology improve with market experience, and come closer to the actual performance as the number of users grows.

of users[22], acts as a self-reinforcing factor in the interest of agents $P_i$ in the technology $T_j$, whose actual performance benefits from the number of users $I_t^j$ itself, is an accurate representation of the bandwagon effect defined earlier.

In random time intervals, using a stochastic process of replacement of obsolete technologies[23], each of the (new and old) producers $P_i$ active in the market in period $t$ decides individually. This means that, as will be discussed below, each producer can either decide to continue with the last technology he decided to install or adopt a new one from the $T_j$ available in the period concerned. For this purpose, in the simulation each active agent $P_i$ at each time $t\left(>0\right)$ is assigned a replacement parameter $ro_t^i$ which takes a value of 1 (replacement) or 0 (continuation) according to a Bernoulli probability distribution $b$ within the group of agents active in that same period. The greater or lesser magnitude of the parameter $b$ allows the model to represent industries with a greater or lesser tendency to technological obsolescence and/or industries in which technological change involves higher or lower costs.

An agent can be considered to have bounded rationality regarding various aspects of the problem, such as his ability to calculate or access to all the information he needs to make a decision. In this model it is possible to argue that despite his imperfect information, the individual agent may *try* to optimize the problem of individual choice. In other words, we assume that each $P_i$ has bounded rationality in terms of access to information, but that given the decision scale he acts *as if* he were optimizing his private decisions[24]. Let us also suppose that $P_i$ agents have heterogeneous preferences regarding the adoption characteristics $C_{Ak}^j$ of the productive technologies. Thus, in each $t$, each $P_i$ adopts[25] the $T_j$ that offers the greatest value in terms of the linear decision[26] function $U_t^i\left(>0\right)$:

$$Max \quad U_t^i = w_1^i \cdot C_{\mathrm{A1t}}^{ij} + w_2^i \cdot C_{\mathrm{A2t}}^{ij} + w_3^i \cdot C_{\mathrm{A3t}}^{ij} + w_4^i \cdot C_{\mathrm{A4t}}^{ij} + w_5^i \cdot C_{\mathrm{A5t}}^{ij} \qquad [10]$$

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[22] Responding to Dalle's (1995) criticism of Arthur's model, the model suggested here does not require that the potential adopter know the *exact number* of users of each technology, but rather it incorporates the advantage of the technology with the greater number of users by means of a function reflecting its better actual performance [4] and a function incorporating the lesser uncertainty [5] surrounding this performance in the performance perceived by the producers.

[23] David and Greenstein, 1990: 6.

[24] According to Nelson (1995: 50), "there is no real difference between saying that companies literally maximize and saying that their behaviour has been learned through trial and error, and in some cases they have been selected by the competitive process. In this way, agents act 'as if' they were maximizing." Using this approximation, for example, Loch and Huberman (1999: 5) assume that "(...) agents are governed by profits but are unable to optimize due to their bounded rationality. [On this assumption] agents simply choose the 'best' of the technologies available, without being able to conduct a full evaluation or anticipate the equilibrium of the system."

[25] In other words, each agent adheres to a "technology population" in Saviotti's sense (2001: 200), which evolves in quantitative terms (size) and qualitative terms (composition).

[26] We apply a simple method of weighted (linear) summation (see, for example, Pomerol and Barba-Romero, 2000: 76).

where the parameters $w^i\left(0<w^i<1\right)$ are the weightings the agent $P_i$ attributes to the various criteria involved in his decision. In the simulation we assume that for each $P_i$ the weightings are normalized, i.e. the condition $\sum w^i=1$ is met; additionally, we assume that the values of each of the weightings $w^i$ that each $P_i$ attributes to each criterion is distributed independently and randomly between the different producers $P_i$ following a $N\left(0{,}1\right)$ distribution within the range of possible values $\left[0{,}1\right]$. We assume that the value of these weightings, which constitute the preference profile of *each agent* $P_i$, do not change over the course of the agent's active life. Nevertheless, the average weightings assigned by the *group* of active agents in each $t$ do change, given that the group changes (quantitatively and qualitatively) as agents enter and leave the market.

Lastly, we define as the standard or dominant technology in $t$ that $T_t^{jST}$ which achieves a market share $\sum_j I_t^j > I^{ST}\%$, for $J_t>2$ technologies[27], for at least $t^{ST}$ periods. We define as a "challenging technology" in $t$ that $T_t^{jR}$ which first exceeds the market share of $T_t^{jST}$, once the latter has ceased to be the standard. Here, $t_r$ (replacement time) is the moment at which $T_t^{jR}$ replaces $T_t^{jST}$ (by exceeding its market share). $F_t^j$ is the actual fitness[28] of technology $j$ at time $t$, defined as $\sum_{Ak} C_{Akt}^j \big/ Ak$. $F_t^{ij}$ is the perceived fitness of technology $j$ (i.e. the average perception of the $i$ users of this technology) at time $t$, defined as $\left(\sum_i\left[\sum_{Ak} C_{Akt}^{ij}\big/ Ak\right]\right)\big/ I_t^j$.

Table 1 recaps the (independent) variables used in the model to characterize the industry represented and the attributes of the technology standardization process (dependent variables), the relationship of which with the independent variables we aim to identify and evaluate.

[27] In the simulation, this condition (*for* $J_t>2$ *technologies*) will only apply in the initial moments after the emergence of the industry given that with a small number of technologies (<2) the fact that one of them obtains more than 50% of adopters may be the result of chance (*first mover advantage*) rather than its merit. However, if later on while one technology is dominant the others reduced their share or disappeared altogether, it would not make sense to say that the non-fulfilment of the condition (*for* $J_t>2$ *technologies*) caused the technology in question to lose its recognition as the standard, given that it had obtained it by its own merits.

[28] Nelson (1995: 64) defines the 'fitness' of a technology as its ability to resolve a specific technology problem better; Saviotti (2001: 207) defines it as the technology's ability to adapt to the environment in which it operates.

Table 1. Recap of the variables and parameters of the model
Characteristics of the industry (independent variables used in the model)

| **Parameter** | **Definition and interpretation** |
|---|---|
| $l_T$ | Average rate at which new available technologies appear during the period in the industry (“average rate of innovation”). |
| $P_T$ | Minimum number of adopters the technology needs to obtain within time $t_T$ in order to survive (“scale of network” necessary). |
| $t_T$ | Maximum time in which a technology needs to obtain $P_T$ adopters in order to survive (“competitiveness of the technology market”) |
| $\bar{r}$ | Average rate of improvement with the adoption of technologies $T_j$ emerging within the same period $t$ (“degree of increasing returns to adoption”) |
| $s_r$ | Dispersion of the average rate of improvement with the adoption of technologies $T_j$ emerging within the same period $t$ (“degree of differentiation in the capabilities of the technology providers”) |
| $l_P$ | Average rate at which new active producers appear in each period (“barriers to entry”). |
| $\bar{s}$ | “Average survival of firms” |
| $s_s$ | Dispersion of the average survival of firms (“competitiveness of the industry”) |
| $c$ | “Rate of communication” between users |
| $b$ | Probability that an agent $i$ replaces his technology $j$ at time $t$ (“tendency to technological obsolescence in the industry”; “cost of technological change in the industry”). |
| $I^{ST}\%$ | Minimum market share –in terms of the relative number of adopters– that a technology needs to achieve during $t^{ST}$ periods in order to be considered the industry’s “standard” technology. |
| $t^{ST}$ | Minimum time a technology needs to maintain the minimum market share $I^{ST}\%$ in order to be considered the industry’s “standard” technology. |

Attributes of the technology standardization process (dependent variables)

| **Variable** | **Definition and interpretation** |
|---|---|
| $t_0^{ST}$ | *Emergence:* for each simulation, the initial moment $t$ in which a technology exceeds a share $I^{ST}\%$ of the active users (for $J_t > 2$) for at least $t^{ST}$ periods, thus becoming the standard. |
| $fr^{ST}$ | *Frequency:* the number of times the above event occurs over the course of each simulation. |
| $v^{jST}$ | *Speed:* for each standard, the time elapsing in the experiment between the entry of a technology in the market and its acceptance as a standard. |
| $d^{jST}$ | *Duration:* for each standard, the time elapsed (greater than $t^{ST}$ periods) during which a technology’s share of users remains above $I^{ST}\%$ (for $J_t > 2$). |
| $p^{jST}$ | *Depth:* for each standard, the maximum share achieved by the technology |

| | |
|---|---|
| | during the time it remains the standard. |
| $dco^{jST}$ | *Susceptibility to changes in supply:* for each standard, the magnitude of improvement necessary in the perceived performance of an alternative technology to break its dominance (percentage variation between $F_t^{ijR}$ and $F_t^{ijST}$ at time $t_r$ ). |
| $dcd^{jST}$ | *Susceptibility to changes in demand:* for each standard, the magnitude of the change in preferences of the users needed to break the dominance of a standard technology. $\forall i \in I^{jR}, \quad \vec{w}^i_{Ak} = (w^i_{A1},\dots,w^i_{Ak}), \quad \vec{w}^{I^{jR}}_{Ak} = \frac{\sum_i \vec{w}^i_{Ak}}{I_t^{jR}}$ <br> $\forall i \in I^{jST}, \quad \vec{w}^i_{Ak} = (w^i_{A1},\dots,w^i_{Ak}), \quad \vec{w}^{I^{jST}}_{Ak} = \frac{\sum_i \vec{w}^i_{Ak}}{I_t^{jST}}$ <br> $\vec{a} = \left\| \vec{w}^{I^{jR}}_{Ak} - \vec{w}^{I^{jST}}_{Ak} \right\|, \quad \vec{b} = \frac{\vec{w}^{I^{jR}}_{Ak} + \vec{w}^{I^{jST}}_{Ak}}{2}$ <br> $dcd^{jST} = \vec{a}\cdot\vec{b} = \sum_k a_{Ak}\cdot b_{Ak}$ at time $t_r$ |

Other model dependent variables

| Variable | Definition and interpretation |
|---|---|
| $F_{t_{ST}}^{jST}$ | Actual fitness of the technology standard $j$ at the time $t_{ST}$ when it becomes the standard. Defined as $\sum_{Akt ST} C_{Akt}^{jST} \big/ Ak$ . |
| $F_{t_{ST}}^{jBAT}$ | Actual fitness of the technology that would have been the best alternative technology $j$, (simultaneously or beforehand) a standard in the $t_{ST}$ moment at which it becomes the standard as such and is adopted by an equivalent number of users. Defined as $\sum_{Akt ST} C_{Akt}^{jBAT} \big/ Ak$ . |

### III.b CALIBRATION OF THE MODEL

Given our interest in its dynamic properties and the difficulty of its mathematical treatment, the agent based model (ABM) described has been developed to run in MATLAB™, a specific mathematics-oriented programming language, recognized for its capabilities and versatility.[29] In keeping with the philosophy of ABM, we have

[29] Our model has been designed to make it straightforward for the analyst to enter the starting-point conditions of the experiment. It is possible to modify the magnitudes of the initial parameters describing the industry (rate of innovation, barriers to entry, rate of increasing returns, etc.) and the general conditions of the experiment (number of dimensions of the technology, number of iterations per simulation and number of simulations per experiment). It also allows a random seed to be saved and reused under different conditions. As well as experimenting with a "base scenario", it is possible to perform multiple sensitivity analyses on the various parameters of the model. Finally, this model generates a wide range of graphics and numerical tables recording the paths taken and giving details of the different perspectives of the process of technological change we are interested in studying. The source

sought to use this flexibility to provide a research methodology to enhance our understanding of the basic processes which might appear in various applications, and not represent or make specific predictions regarding a particular empirical application. Thus, when calibrating the model (base scenario) we opted for a set of theoretically acceptable parameters obtained from the literature, but which are not intended to represent precisely any particular situation or industry. The subsequent sensitivity analysis will make it possible to evaluate statistically the effect of modifications on this base scenario.

As regards $I^{ST}\%$, Anderson and Tushman (1990) consider a dominant design (standard) to have emerged when a new architecture obtains 50% or more of the installed processes[30] and maintains this market share for at least 3 consecutive years[31]. Various studies of different industries in a number of countries (Klepper and Simons, 1997; Gort and Klepper, 1982) confirm that a value of 15 for the parameter $l_P$ may be theoretically acceptable for the base scenario. As regards the parameters $\bar{s}$ and $s_s$, studies such as those by Klepper and Simons (1997), Mata and Portugal (1994) or Tegarden et al. (2000) suggest that values in the base scenario for $\bar{s}$ and $s_s$ of 5 and 2 years, respectively, are of a theoretically acceptable order of magnitude. Klepper and Simons (1997) also offer guidance as to an approximate magnitude for $l_T$. In the base scenario we have opted for a value of 1.

Unlike the previous parameters, which are populational, and whose magnitudes can be justified from empirical studies, the way the underlying assumptions were decided for the remainder of the initial parameters in the model was more *ad hoc*. Where possible, we have sought to justify the values used on the basis of the preceding values. In this way, given the magnitude (justified) of the entry and exit of firms to and from the industry, which leads the industry to stabilize in the base scenario with a population of almost 80 firms which are constantly being renewed, we believe it reasonable that a technology should be adopted by at least 5 firms ($P_T$) within 2 years ($t_T$) in the base scenario in order for it not to be considered "rejected" by the productive system and for network economies to come into play, allowing it to compete with the other technologies. Given this value of $P_T$, if we ascribe a value of 0.2 to the maximum dispersion $s_{Akt}^{j}$ of the perceived performances $C_{Akt}^{ij}$ around the actual performance of a technology $C_{Akt}^{j}$ ($\in [0,1]$), according to expression [5] the rate of communication $c$ should have a value of 0.8. In the same way, if the maximum values that can be achieved by $\hat{C}_{Ak}^{j}$ and $C_{Ak_0}^{j}$ are 1 and 0.5, respectively, from expression [4] we can deduce that a rate $\bar{r}$ of around 0.5 places the "frontier of technological improvement" at approximately 50% in an industry of 80 firms. In other words, we are assuming that only one technology standard can reach its full performance potential, which, at all

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code of the model can, of course, be requested from the author, together with the technical details of the modular structure of the program, the names and descriptions of the model's variables, and the routines it contains.

[30] This condition can obviously only be obtained by one technology at any time .

[31] In their various studies Anderson and Tushman vary this figure between 3 and 4 years.

events, is limited (<1). We also establish a deviation $s_r = 0.2$ to ensure a certain degree of diversity between the technological alternatives.

Lastly, the value of 0.2 assigned to $b$ (probability that agent $i$ replaces his technology $j$ at time $t$) in the model is justified by the relative tendency to technological obsolescence and the considerable costs of technological change in the industry.

### III.c NUMERICAL SIMULATIONS

In order to fulfil the aims of the investigation and check the hypotheses set out below, we ran an experiment using the base scenario, involving 150 simulations of 50 iterations each, using different random seeds in each simulation[32]. As a sample, and for reasons of space, Appendix 1 presents only the first 10 simulations of all the standards recorded in each simulation. The table in the appendix shows the different characteristics of each of the standards, and the complete standardization process, recorded in each "history" (simulation) of this industry, according to the attributes described above (time, frequency, speed, duration, depth, susceptibility to changes in supply and in changes in demand). Appendix 2 shows the data for the first standard recorded in each simulation, filtered out from the general results of the 150 simulations. The characteristics of these standards will be examined in more detail below[33].

The set of graphs included in Appendix 3 shows the results of a typical model simulation using the base scenario. The first graph shows the time course of the adoption (market shares as a unit proportion) of the technologies by the various producers present in each moment in the industry producing good *X*. Following Anderson and Tushman (1990), technologies that exceed a 50% share for at least 3 periods are identified as technology standards[34]. The last two graphs show the evolution

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[32] To decide on the appropriate number of simulations in the main experiment we first ran a pilot in which 15 simulations were run on the base scenario with different random seeds. This pilot experiment yield standard deviations of $s$ for the variables $F_{t_{ST}}^{jST}$, $F_{t_{ST}}^{jBAT}$, $dco^{jST}$, $dcd^{jST}$, $das$ and $dac$, involved in the hypotheses H1, H2, H3 and H4. When a confidence of 95% was required ($z_a = 1.96$), for reasonable amplitude intervals of $d$, the variable requiring the largest sample $n$ was $dco^{jST}$, which required a sample of around 70 cases of at least one standard (see the following note), an objective that in our base scenario required approximately 150 simulations:

$$P(\bar{x} - \frac{s \cdot z_a}{\sqrt{n}} \le m \le \bar{x} + \frac{s \cdot z_a}{\sqrt{n}}) = 1 - a \qquad \rightarrow \qquad d = \frac{s \cdot z_a}{\sqrt{n}} \qquad \rightarrow \qquad n = \frac{s^2 \cdot z_a^2}{d^2}$$

As regards the choice of 50 iterations per simulation, this number was selected because it was considered a sufficiently distant horizon to enable the phenomenon of a series of successive standards to be studied. A remoter horizon did not yield different conclusions, but required more computation time in the experiments.

[33] We consider the first standard to be representative of the characteristics of the rest of the standards in the same simulation, and given that it is the one produced in the greatest number of simulations, its choice ensures the greatest number of data. Those standards that emerge at the start of the experiment and continue to dominate through to the end are considered outliers and discarded.

[34] The number next to the word "standard" (simulator otputs in spanish: "estándar") identifies the technology in question and represents its order of appearance in the history of the industry shown.

of the population of firms and the population of technologies, respectively. It is worth highlighting the striking visual isomorphism between the results of the model and the patterns of the phenomenon observed in real industries as, according to Marney and Tarbert (2000), this may be considered an indicator of the validity of the model. In a test of *external validity*, as understood by Kleijnen (1998), in Appendix 4 it is possible to see that our model offers a representation of the phenomenon of technological succession consistent with the empirical evidence on the diffusion of technologies in industries as diverse as RAM chips, steel manufacturing or power generation.

Unlike conventional models of technology diffusion and standardization, which focus on the *rate* at which *one* new technology diffuses until it is fully adopted, our model enables a broader approximation to the *process* of technological change to be obtained, from the perspective of the *extension* of the diffusion of *multiple* alternative technologies and the related phenomenon of standardization. Previously, we pointed out that in addition to Arthur, many other authors have portrayed the technology selection process as an "all or nothing" story (Abrahamson and Rosenkopf, 1997). This is a general shortcoming of diffusion and standardization models that has been pointed out repeatedly in various studies over the last decade (Schilling, 2002: 395; Jaffe et al., 2000: 41; Windrum and Birchenhall, 1998: 112; David, 1997: 36; Nelson, 1994b; David and Greenstein, 1990: 8). Despite the various forces (*positive feedbacks*) that help reinforce the dominant position of a technology standard, experience shows that no standard remains in place in an industry indefinitely (Abrahamson and Rosenkopf, 1997; Ruttan, 1997; Witt, 1997; Grübler, 1990; Ausubel, 1989). On the contrary, in reality, if a long enough horizon is taken, one sees a succession of standards, a dynamic of transition between unstable equilibria, which this model is able to represent and characterize.

It is rare for a technology standard to achieve absolute diffusion in an industry, where this is understood to mean a 100% market share. By contrast, one often observes how different degrees of standard coexist with less successful technological alternatives, which may survive for a variable length of time in market niches (Grübler, 1990; Dalle, 1995; Freeman, 1996). The existence of these niches is explained both by the emergence of new alternatives, which start to build their own installed user base, and by the heterogeneity of users' preferences, which may circumstantially maintain different groups apart from the dominant standard. Again, the proposed model makes it possible to show in greater detail than conventional "all-or-nothing" models (which, moreover, usually focus on the competition between just two alternatives) the reality of an industry divided at all times between multiple available alternatives, all with different levels of adoption at each moment in time.

## IV. EXAMINATION OF HYPOTHESES

It was argued above that in the presence of increasing returns to adoption the market may become locked-in in favour of one of the competing alternatives due to historical circumstances. It is a recurring statement in the literature on this issue that under these conditions there is no guarantee that there are no alternatives to the winning technology that would have had lower unit costs if they had achieved an equivalent position of market dominance (Arthur, 1989; David, 1989; Cowan, 1990; Metcalfe, 1994).

Moreover, throughout this paper we have maintained that the technology path followed by an industry is shaped by chance historical events (*path dependency*). Thus we can state that the distribution of market shares between the different technological alternatives at any given time, and the succession of possible technological standards, will depend on the one hand on the chance order in which these alternatives are available for adoption and that in which the potential adopters enter and exit the industry. It will also depend on the characteristics of each of these heterogeneous "populations" (technologies and firms) at each time (performances and preferences, respectively).

**Hypothesis 1.** In an industry characterized by increasing returns to technology adoption, over a sufficiently long time horizon, we will witness a succession of multiple alternative equilibria (standards), which cannot be anticipated and are not necessarily Pareto-optimal.

**Proof.** In the table of general results in Appendix 1 it is possible to see how the different "histories" of the industry represented by the various simulations do indeed show alternative technological paths which cannot be anticipated in advance. The data in column 2 of the table (ID_ST, identifier of standard $j$) show that in the various simulations (SIM is the number of the simulation) different standards emerge, each of them characterized by a different initial performance vector $\vec{D}_{t_0}^{j}$ (columns 5 to 9). Under the same initial conditions, with an identical base scenario, the element of chance in the evolution of the populations of technologies and adopters (order of entry and exit, characteristics, preferences, etc.) leads the different simulations ("histories" of the industry) to different standard technologies in each case. Clearly, these paths of technological change cannot be anticipated by the agents participating in the industry, as their course depends on unpredictable events. In this respect the model presented here overcomes the determinism to which the traditional assumptions leads and allows this theoretical exercise to be performed in a way which shows how different sequences of events in the same industry can lead to different technology paths.

With regard to the second part of Hypothesis 1, the possible non-Pareto-optimal nature of the equilibria (standards) arrived at implies that as a result of the presence of increasing returns to adoption, uncoordinated adoption decisions by mutually influenced producers may lead the industry, in a dynamic conditioned by the way events unfold, to an inferior technology standard than that which could have been achieved had they chosen one of the available alternatives in a coordinated way (Arthur, 1989; Cowan, 1990; David, 1993). Obviously, *ex post* it is impossible to confirm or refute this statement empirically (Nelson, 1994a: 141). Under certain reasonable assumptions the model presented allows a counter-factual exercise comparing the performance of a dominant technology at the time when it becomes the standard and the hypothetical performance that the other alternatives coexisting with it or preceding it would have achieved if they had been adopted by an equal number of users. Column 10 (FIT_ST, $F_{t_{ST}}^{jST}$ ) of Appendix 2 shows the actual fitness of the technological standard (column 2, ID_ST) at the moment (column 3, TST) at which it becomes the standard. Column 11 (FIT_BAT, $F_{t_{ST}}^{jBAT}$) shows the actual fitness the best alternative technology from among those coexisting with or preceding the technology when it became the standard would have achieved (column 12, ID_BAT) had it been adopted by an equal number of users. It can be seen that in a significant[35] number of cases FIT_BAT exceeds FIT_ST, which leads us also to accept the second part of Hypothesis 1.

As described earlier, on Anderson and Tushman's (1990) view of the technology cycle, the transition between two standards is usually presented as the result of a technological discontinuity. In Foster's terms (1986), there needs to be a "jump" of a certain order of magnitude between two S-shaped technology performance curves. Other authors have also suggested that it is necessary for there to be a significant improvement in the performance of an alternative to the standard in order to overcome the inertia of the system and initiate the transition from a locked-in technology to a new one (Grove, 1996; Drucker, 1993). A number of empirical studies have tried to quantify this order of magnitude in specific industries and historical circumstances. One frequently cited example is that of David (1985), who concluded that 20-30% savings were insufficient to cause a transition from the QWERTY system to the Dvorak keyboard. However, we do not have a formal generalizable observation of this fact in technology transitions. This model enables us to examine statistically whether this is the case. It also makes it possible to measure, as will be shown below, the relationship between the magnitude of the improvement necessary to produce a technology transition and the different characteristics of the various industries in which a transition of this kind takes place (rates of innovation, barriers to entry, etc.)

**Hypothesis 2.** The emergence of an alternative to the locked-in technology (standard) that offers a sufficient improvement in its characteristics (technology supply side), can lead the cumulative endogenous phenomena in the industry, which derive from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry.

**Proof.** Column 15 of the table of results in Appendix 2 shows, for each standard, its susceptibility to changes in supply ($dco^{jST}$), previously defined as the magnitude of the necessary improvement in performance for an alternative technology to break its dominance (percentage variation in $F_t^{ijR}$ and $F_t^{ijST}$ at time $t_r$). In an interval of confidence of 95% for the average between 17.07 and 32.78, the variable $dco^{jST}$ takes an average value of 24.93% in the base scenario, with a standard error of 3.94. According to results of a T-test (t=6.330; bilateral significance < 0.01) the average of the sample is statistically non-zero and the value 0 is outside the confidence interval. In other words, the model confirms Hypothesis 2: the emergence of an alternative

[35] It is not, however, a *statistically* significant number of cases. In column 8 of Appendix 2 the dichotomous variable FST_FB1 = 1 when FIT_BAT > FIT_ST and = 0 otherwise. According to the results of a non-parametric (binomial) analysis of proportionality on FST_FBI which does not allow us to state that the proportion of zeroes is different from that of ones for any reasons other than chance (bilateral asymptotic significance = 0.644). Given that FIT_BAT and FIT_ST are distributed normally, we also performed a T-test for independent samples (for this purpose the variable FST_FB2 was created, with values 1 and 2 for each group) throwing up an equivalent result as that in the previous comparison (t=-1.408; sig. bil.=0.161). At all events, to accept this second part of H1 it is enough to demand that FIT_BAT is greater than FIT_ST on at least one occasion, as in fact happens.

technology to the locked-in technology (standard) which presents a sufficient improvement in its characteristics (in this base scenario, of the order of 25%) can cause the system to escape the lock-in endogenously (technology supply side).

However, the evidence (Kemp, 1997: 281; Cowan and Hulten, 1996) reveals that a technology standard's loss of the dominant position is not always solely due to the emergence of an alternative offering significantly better performance. To obtain a more realistic view of the internal processes explaining the dynamics of diffusion and the succession of standards, the proposed model also incorporates the importance of possible changes on the *demand side*, which it represents as changes in the preferences of the possible adopters.

**Hypothesis 3.** A sufficient change in the average preferences of potential adopters regarding the features of technologies (technology demand side), can lead the cumulative endogenous phenomena in the industry, which derives from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry..

**Proof.** Column 16 of the table of results in Appendix 2 shows, for each standard, its susceptibility to changes in demand ($dcd^{jST}$), defined above as the magnitude of the necessary change in user preferences to break its dominance (see *table 1*). Within an interval of confidence of 95% for the average between 2.84 and 3.95, the variable $dcd^{jST}$ takes an average value of 3.40%, with a standard error of 0.28. According to results of a T-test (t=12.261; bilateral significance < 0.01) the average of the sample is statistically non-zero and the value zero is outside the confidence interval. In other words, the results of the model confirm H3: a sufficiently large change in the average preferences of potential adopters regarding technology features (in this base scenario, of the order of 3.5%) can cause the system to escape the lock-in endogenously (technology demand side).

We will now look at the final objective of this study. To identify and evaluate the relationships between the main characteristics of the industry and the attributes of the technology standardization process (Table 1), six different sensitivity[36] analyses were carried out on the effects of incremental modifications in the parameters $l_T$, $\bar{r}$, $ß$, $l_P$, $\bar{s}$ and $c$ on the variables $t_0^{ST}$, $f^{ST}$, $v^{jST}$, $d^{jST}$, $p^{jST}$, $dco^{jST}$, and $dcd^{jST}$. Table 2 shows a summary of the results of the 42 regressions.

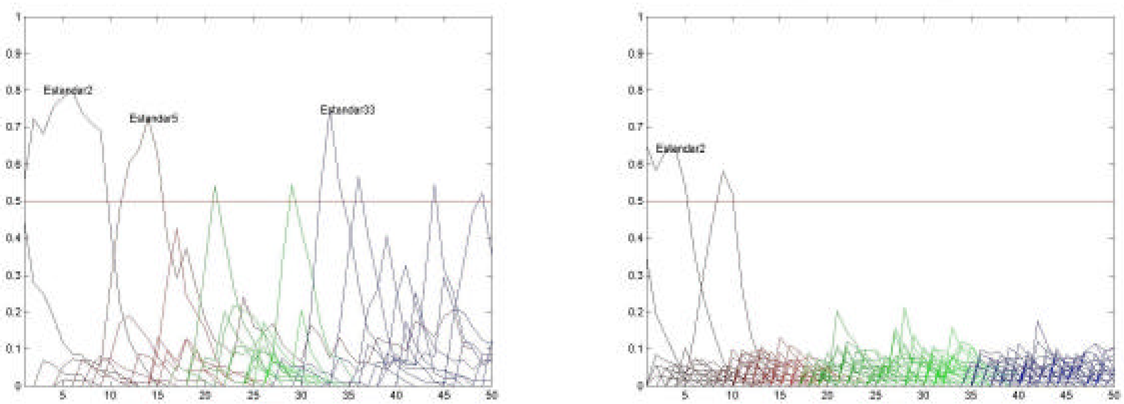
[36] Five values were taken for each parameter analysed and 30 simulations performed for each value (in total, 150 simulations for each analysis), holding the rest of the parameters unchanged and using the same random seed in all the simulations.

Table 2. Summary of the results of the sensitivity analysis
(**significant relationship with a level of confidence of 99%; * ditto for 95%)

Effect on the variable

| Incremental modifications in the parameter | | $t_0^{ST}$ | $f^{ST}$ | $v^{jST}$ | $d^{jST}$ | $p^{jST}$ | $dco^{jST}$ | $dcd^{jST}$ |
|---|---|---|---|---|---|---|---|---|
| $l_T$ | $b$ | 0,076 | -0,482 | 0,076 | -0,441 | -0,615 | -0,121 | 0,046 |
| | $t$ | 0,688 | -4,995** | 0,688 | -4,423** | -7,014** | -1,096 | 0,418 |
| $\bar{r}$ | $b$ | -0,525 | 0,308 | -0,585 | 0,335 | 0,524 | 0,013 | -0,106 |
| | $t$ | -7,011** | 3,672** | -8,196** | 4,039** | 6,994** | 0,143 | -1,211 |
| ß | $b$ | -0,215 | -0,183 | -0,632 | -0,499 | 0,519 | -0,552 | 0,051 |
| | $t$ | -1,589 | -1,342 | -5,873** | -4,154** | 4,379** | -4,778** | 0,356 |
| $l_P$ | $b$ | 0,580 | 0,308 | 0,383 | 0,450 | 0,407 | 0,014 | -0,471 |
| | $t$ | 7,226** | 3,288** | 4,208** | 5,108** | 4,527** | 0,144 | -5,424** |
| $\bar{s}$ | $b$ | 0,179 | -0,207 | 0,179 | 0,651 | -0,010 | 0,076 | 0,166 |
| | $t$ | 2,020* | -2,346* | 2,020* | 9,521** | -0,114 | 0,850 | 1,866 |
| $c$ | $b$ | -0,370 | -0,188 | -0,370 | -0,404 | 0,228 | 0,127 | 0,035 |
| | $t$ | -3,623** | -1,742 | -3,623** | -4,030** | 2,129* | 1,168 | 0,313 |

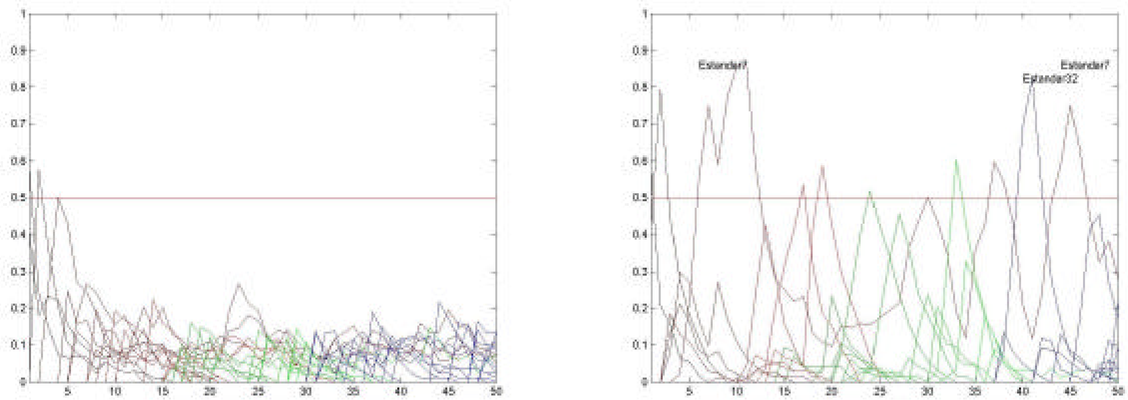
Certain industries show greater dynamism than others in terms of the introduction of new technological innovations in their production processes. According to the (significant) results of testing the sensitivity of $l_T$, in industries (or in phases of the lifetime of an industry) with a high *innovation rate* the standards show a tendency to appear with less often, have a shorter duration and achieve a smaller share (Table 2 and Figure 4). The existence of a larger number of alternatives, and the faster rate of renewal, makes it difficult for any of them to achieve sufficient market share to enable them to differentiate themselves from the rest. Any advantage a technology achieves is slight, and is soon threatened by the emergence of new alternatives which may prove more attractive.



($l_T = 1$) ($l_T = 5$)

Fig. 4. Sensitivity analysis of $l_T$, innovation rate
(showing only range ends; typical results; time course of market shares)

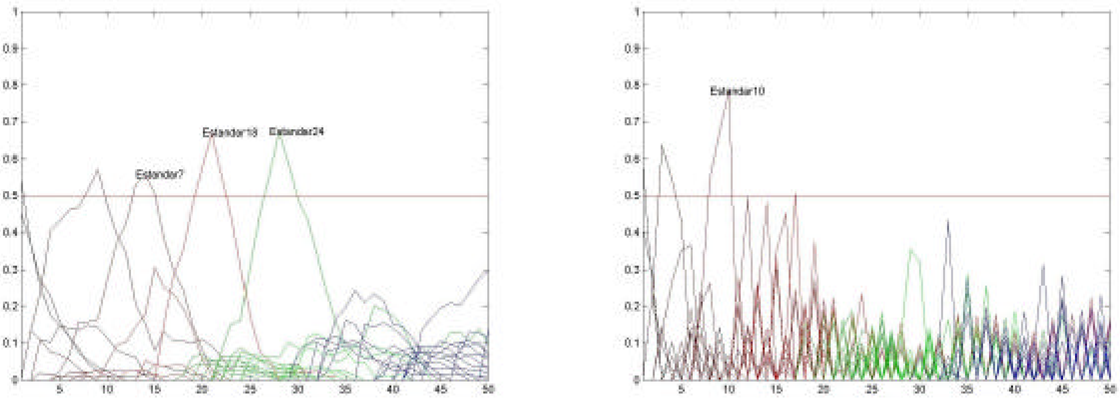
The presence of increasing returns to the adoption of technology is greater in productive sectors in which technology is integrated and systemic in nature, has a long history and special infrastructure requirements. The significant results of the sensitivity of $\bar{r}$ reveal that in industries (or in phases of the lifetime of an industry) with a higher average rate of *increasing returns to adoption,* standards show a tendency to appear earlier and more often, develop more rapidly, last longer and achieve a larger market share (Table 2 and Figure 5). As might be expected, in a new test of the consistency of the model, a greater intensity of the factors we have argued are the source of the phenomenon investigated, results in an intensification of the phenomenon. The sign of the relationships has been discussed sufficiently over the course of the study, and is consistent with the empirical evidence. Also, we have confirmed in numerous experiments that in the presence of constant returns to adoption ($\bar{r} = 0$) no standards appear in the model (or they do so only exceptionally in the early periods).



($\bar{r} = 0$) ($\bar{r} = 1$)

Fig. 5. Sensitivity analysis of $\bar{r}$, increasing rate of return
(showing only range ends; typical results; time course of market shares)

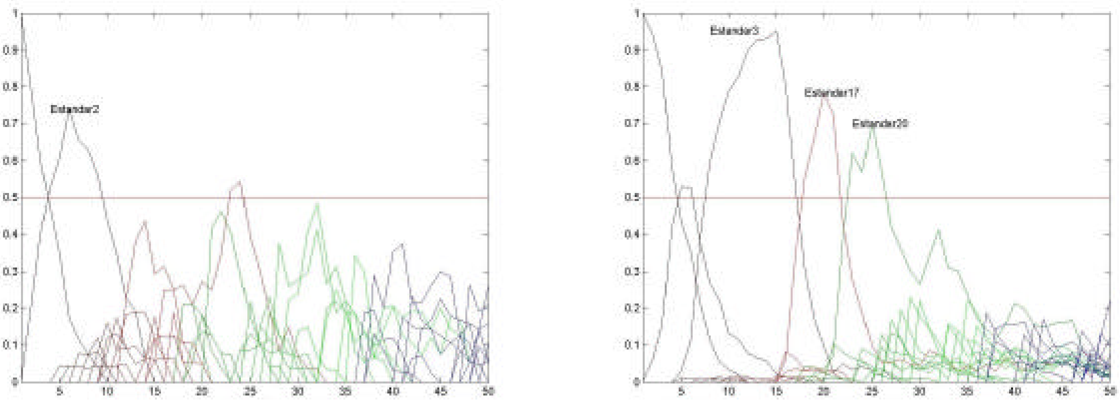
The frequency with which production technologies are renewed varies between different industries as a function of the rate at which plant and equipment becomes obsolete and of the cost of their replacement. The (significant) results of an analysis of the sensitivity of *ß* show that in industries (or in phases of the lifetime of an industry) with a higher *frequency of technology renewal* (due to the faster rate of obsolescence and/or lower cost of changing technology), standards show a tendency to develop more rapidly, last for a shorter time and achieve a larger market share (Table 2 and Figure 6). When firms want or have to (and are able to) renew their plant and equipment more frequently, the process of adhesion to an alternative may be accelerated and intensified, although the limited loyalty of adopters makes standards short-lived. Proof of this is the additional result showing that in industries with a greater frequency of technology renewal, standards are more vulnerable to improvements in the features offered by alternative technologies.




( *ß=0*) ( *ß=1*)

Fig. 6. Sensitivity analysis of *ß*, frequency of renewal
(showing only range ends; typical results; time course of market shares)

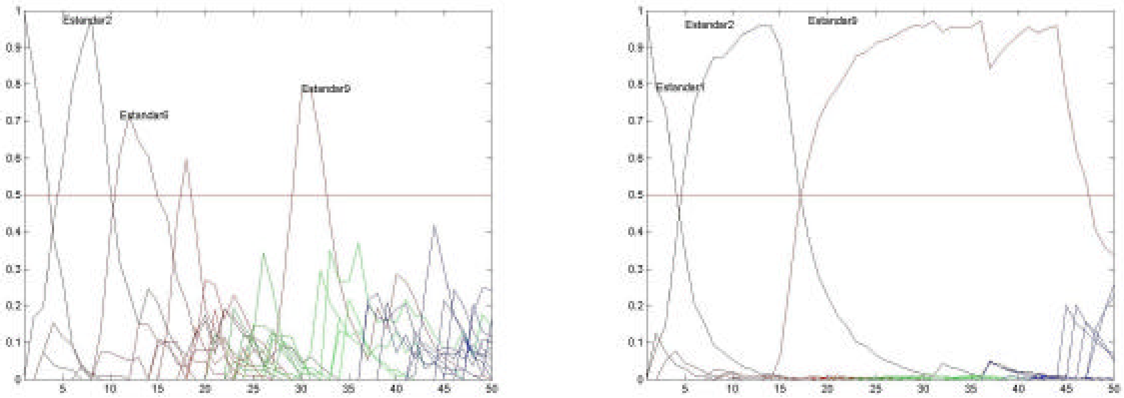
Some industries are more accessible than others to new firms that want to enter and establish themselves in the sector. The (significant) results of examining the sensitivity of $l_P$ reveal that in industries (or in phases of the lifetime of an industry) with lower *barriers to entry* for users, standards show a tendency to appear later and less often, develop more slowly, last for a shorter time and achieve a smaller market share (Table 2 and Figure 7). As might be expected, given the heterogeneity of the adopters, the larger the number of adopters the harder it is to converge on a first standard. However, once a given user base has been established, the flow of new entrants is readily channelled towards the agreement established by the previous users, strengthening its reach and duration. The results also show that standards in accessible industries are more likely to succumb to changes in users' preferences. It may be deduced that, given the constant renewal of the user base, the standard is more likely to strengthen its position if the heterogeneity of the adopters' preferences remains relatively stable.




( $l_P = 5$) ( $l_P = 25$)

Fig. 7. Sensitivity analysis of $l_P$, rate of entry of adopters
(showing only range ends; typical results; time course of market shares)

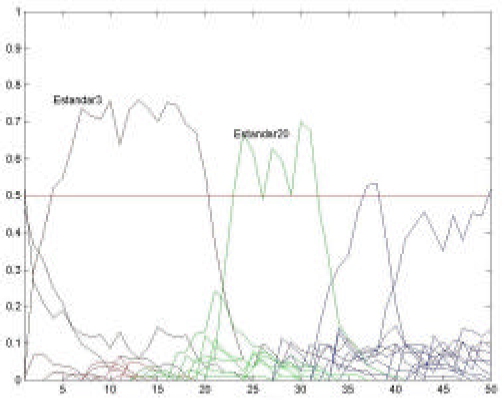
Industries in which, for various reasons, there is less competitive pressure, show lower rates of exit by firms. The (significant) results of the sensitivity analysis of $\bar{s}$ reveal that in industries (or in phases of the lifetime of an industry) with higher *survival rates* among users, standards show a tendency to appear later and less often, develop more slowly and last for a longer time (Table 2 and Figure 8). As in the previous analysis, given the heterogeneity of the adopters, the larger the number of adopters the harder it is to converge on an initial standard. However, in this case, under the (restrictive) assumption made in the model that users' preferences remain constant, there is greater certainty of stability of the heterogeneity of the user base, and thus greater duration and lower frequency of replacement of standards.

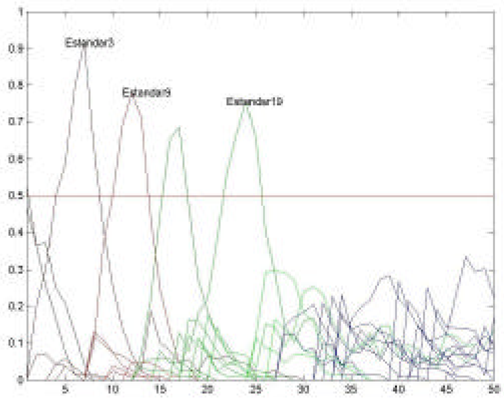


($\bar{s} = 5$) ($\bar{s} = 25$)

Fig. 8 Sensitivity analysis of $\bar{s}$, survival rate
(showing only range ends; typical results; time course of market shares)

Reasons intrinsic to the technologies (complexity, observability) or the nature of the industry (geographic dispersion, transparency) may imply different degrees of communication of experience between users and potential adopters. The significant results of the sensitivity of $c$ reveal that in industries (or in phases of the lifetime of an industry) with a higher degree of *communication between users*, standards show a tendency to appear earlier, develop more rapidly, last for a shorter time and achieve a larger market share (Table 2 and Figure 9). A higher degree of communication of experiences reduces uncertainty and reduces the information search costs while also ensuring potential users are more knowledgeable about the technology. Consequently, initial convergence around an alternative, and successive agreements, are reached easily and are deep. However, the reduced uncertainty also enables adopters to recognize and back new alternatives early on, which means that standards in this type of industry do not tend to be long-lasting.




( $c = 0$ ) ( $c = 1{,}6$ )

Fig. 9. Sensitivity analysis of $c$, rate of communication
(showing only range ends; typical results; time course of market shares)

As we hope to have shown, within its limitations, this relatively simple model enables a broad and consistent characterization or taxonomy of the relationships between the circumstances of an industry and the attributes of the processes of technological standardization operating in it. The results of the simulation have allowed us to corroborate a number of intuitions from economics while drawing attention to less obvious relationships, suggesting possible lines of empirical research to confirm and expand on the conclusions obtained.

## V. CONCLUSIONS

Conventional models of technology diffusion and standardization have typically focused on the question of the *rate* of diffusion at which *one* new technology is fully adopted. The model presented here provides a broader approach to the process of technological change, from the perspective of the *extension* of the diffusion of *multiple* alternative technologies, and the related phenomenon of standardization.

Experience shows that no standard remains in place in an industry indefinitely, and it is unusual for a technology standard to achieve total diffusion. By contrast, in reality, over a sufficiently long horizon it is possible to observe a succession of standards of differing degrees that coexist with less successful alternative technologies, which may survive for varying lengths of time in niche markets. The proposed model makes it possible to show with greater detail than conventional "all-or-nothing" models (which, moreover, usually focus on the competition between just two alternatives) the reality of a dynamic of transition between unstable equilibria in an industry divided at all times between multiple available alternatives, all with different levels of adoption at each moment in time.

It is a recurring theme in the literature on technology diffusion that in the presence of increasing returns to adoption the market may become locked-in in favour of one of the competing alternatives are a result of historical circumstances. There is no guarantee that there are no alternatives to the winning technology that would have had lower unit costs if they had achieved an equivalent position of market domination. The model has allowed us to examine the hypothesis that in an industry characterized by increasing returns to adoption of technology, over a sufficiently long time horizon, we will witness a succession of multiple alternative equilibria (standards), which cannot be anticipated and are not necessarily Pareto-optimal.

Various authors have also suggested that it is necessary for there to be a significant improvement in the performance of an alternative to the standard to overcome the inertia of the system and initiate the transition from a locked-in technology to a new one (*supply side*). Although a number of empirical studies have attempted to quantify this order of magnitude in specific industries and historical moments, there is no formal or generalizable confirmation of this fact in technology transitions. The evidence also shows that the loss of dominant position by a technology standard is not always *solely* due to the emergence of an alternative technology offering significantly better performance. It may also be due to changes on the technology *demand side*. The proposed model has also allowed us to examine the hypothesis that either a *sufficient improvement in the features* of alternative technologies or a *sufficient change in the preferences* of potential adopters regarding the features of technologies can lead the cumulative endogenous phenomena in the industry, deriving from the presence of increasing returns to adoption, to break with the standard and trigger the transition towards the next standard, without the need for intervention from outside the industry.

Most research into factors influencing the technology diffusion process has concentrated on the characteristics of the *technologies* and the characteristics of adopting *firms*. In the literature there are, however, relatively few approximations to the way in which the aggregate characteristics of the *industry* or sector affect the process of technological diffusion (and in particular the dynamic of standardization). The few sectorial studies that exist, most of which are empirical, generally use average characteristics of the firms belonging to the sector and also offer somewhat inconclusive and even at times contradictory results. The model proposed here has enabled a wide-ranging and consistent characterization or taxonomy of the relationships between the circumstances of an industry and the attributes of the technology standardization processes taking place within it. It has also corroborated a number of intuitions from economics, while drawing attention to some less obvious relationships which may be an interesting focus for further research.

Appendix 1. Experiment using the base scenario, 150 simulations of 50 iterations each, using different random seeds in each simulation (sample of the first 10 simulations)

| *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* | *11* | *12* | *13* | *14* | *15* | *16* | *17* | *18* | *19* | *20* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **SIM** | **ID_ST** | **TST** | **TFST** | **CA01** | **CA02** | **CA03** | **CA04** | **CA05** | **FIT_ST** | **FIT_BAT** | **ID_BAT** | **FST** | **VST** | **DST** | **PST** | **ID_TRET** | **TR** | **DCO** | **DCD** |
| 1 | 1 | 3 | 50 | 0,254 | 0,451 | 0,101 | 0,157 | 0,329 | 0,650 | 0,692 | 3 | 1 | 0 | 47 | 0,988 | | | | |
| 2 | 1 | 2 | 50 | 0,058 | 0,422 | 0,478 | 0,366 | 0,269 | 0,716 | 0,576 | 2 | 1 | 0 | 48 | 0,989 | | | | |
| 3 | 2 | 2 | 11 | 0,469 | 0,390 | 0,272 | 0,370 | 0,397 | 0,722 | 0,674 | 3 | 3 | 1 | 9 | 0,847 | 9 | 12 | -2,425 | 6,722 |
| 3 | 9 | 16 | 20 | 0,443 | 0,127 | 0,416 | 0,041 | 0,190 | 0,488 | 0,769 | 8 | 3 | 11 | 4 | 0,667 | 17 | 24 | -2,425 | 3,307 |
| 3 | 9 | 47 | 50 | 0,443 | 0,127 | 0,416 | 0,041 | 0,190 | 0,508 | 0,866 | 28 | 3 | 40 | 3 | 0,688 | | | | |
| 4 | 3 | 4 | 10 | 0,191 | 0,410 | 0,134 | 0,350 | 0,292 | 0,746 | 0,723 | 5 | 2 | 3 | 6 | 0,667 | 12 | 9 | 1,980 | 4,213 |
| 4 | 14 | 16 | 19 | 0,464 | 0,412 | 0,155 | 0,082 | 0,178 | 0,679 | 0,746 | 3 | 2 | 4 | 3 | 0,730 | 20 | 20 | 1,980 | 2,228 |
| 6 | 1 | 28 | 34 | 0,244 | 0,264 | 0,440 | 0,185 | 0,208 | 0,499 | 0,781 | 14 | 2 | 27 | 6 | 0,713 | | | | |
| 6 | 1 | 35 | 43 | 0,244 | 0,264 | 0,440 | 0,185 | 0,208 | 0,499 | 0,781 | 14 | 2 | 34 | 8 | 0,713 | | | | |
| 7 | 13 | 15 | 18 | 0,188 | 0,282 | 0,405 | 0,418 | 0,486 | 0,579 | 0,699 | 2 | 1 | 4 | 3 | 0,667 | 20 | 24 | 56,295 | 6,936 |
| 8 | 2 | 2 | 6 | 0,497 | 0,248 | 0,201 | 0,147 | 0,476 | 0,766 | 0,731 | 4 | 1 | 1 | 4 | 0,907 | 6 | 5 | -5,472 | 2,659 |
| 9 | 4 | 7 | 10 | 0,145 | 0,089 | 0,252 | 0,394 | 0,082 | 0,670 | 0,751 | 5 | 1 | 4 | 3 | 0,733 | 5 | 10 | -2,368 | 5,021 |
| 10 | 1 | 21 | 32 | 0,261 | 0,144 | 0,388 | 0,124 | 0,333 | 0,538 | 0,782 | 8 | 2 | 20 | 11 | 0,737 | | | | |
| 10 | 1 | 44 | 50 | 0,261 | 0,144 | 0,388 | 0,124 | 0,333 | 0,538 | 0,782 | 8 | 2 | 41 | 6 | 0,737 | | | | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

Equivalence between statistical abbreviations (SPSS) and model variables

| SPSS | Model |
|---|---|
| SIM | Number of simulation |
| ID_ST | Identifier of standard technology |
| TST | Standard emergence ( $t_0^{ST}$ ) |
| TFST | Standard end |
| CA01 | Starting level of performance of $T^{jST}$ in criteria 1 ( $C^{jST}_{Ak_0}, k=1$ ) |
| CA02 | ditto $k=2$ |
| CA03 | ditto $k=3$ |
| CA04 | ditto $k=4$ |
| CA05 | ditto $k=5$ |
| FIT_ST | Actual fitness ( $F_t^j$ ) of the technology standard at the time $t_0^{ST}$ |
| FIT_BAT | ditto of the BAT at the time $t_0^{ST}$ |
| ID_BAT | Identifier of best alternative technology |
| FST | Frequency ( $f^{ST}$ ) |

| SPSS | Model |
|---|---|
| VST | Speed ( $v^{jST}$ )* |
| DST | Duration ( $d^{jST}$ ) |
| PST | Depth ( $p^{jST}$ ) |
| ID_TRET | Identifier of challenging technology |
| TR | Replacement time ( $t_r$ ) |
| DCO | Susceptibility to changes in supply ( $dco^{jST}$ )* |
| DCD | Susceptibility to changes in demand ( $dcd^{jST}$ )* |

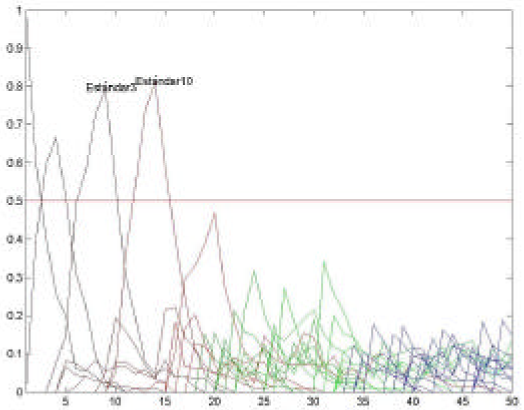
* Note: higher numbers indicate lower levels

Appendix 2. Data for the first standard recorded in each simulation, filtered out from the general results of the 150 simulations

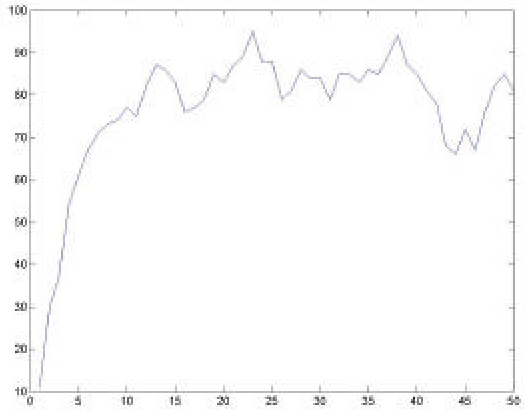
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **SIM** | **ID_ST** | **TST** | **TFST** | **FIT_ST** | **FIT_BAT** | **ID_BAT** | **FST_FB1** | **FST** | **VST** | **DST** | **PST** | **ID_TRET** | **TR** | **DCO** | **DCD** |
| 3 | 2 | 2 | 11 | 0,722 | 0,674 | 3 | 0 | 3 | 1 | 9 | 0,847 | 9 | 12 | -2,425 | 6,722 |
| 4 | 3 | 4 | 10 | 0,746 | 0,723 | 5 | 0 | 2 | 3 | 6 | 0,667 | 12 | 9 | 1,980 | 4,213 |
| 7 | 13 | 15 | 18 | 0,579 | 0,699 | 2 | 1 | 1 | 4 | 3 | 0,667 | 20 | 24 | 56,295 | 6,936 |
| 8 | 2 | 2 | 6 | 0,766 | 0,731 | 4 | 0 | 1 | 1 | 4 | 0,907 | 6 | 5 | -5,472 | 2,659 |
| 9 | 4 | 7 | 10 | 0,670 | 0,751 | 5 | 1 | 1 | 4 | 3 | 0,733 | 5 | 10 | -2,368 | 5,021 |
| 14 | 3 | 1 | 10 | 0,557 | 0,464 | 2 | 0 | 1 | 0 | 9 | 0,862 | 7 | 11 | 49,904 | 7,169 |
| 15 | 2 | 4 | 7 | 0,787 | 0,786 | 3 | 0 | 2 | 3 | 3 | 0,563 | 3 | 6 | 2,374 | 7,302 |
| 16 | 2 | 6 | 10 | 0,698 | 0,684 | 8 | 0 | 3 | 4 | 4 | 0,616 | 12 | 10 | 60,655 | 4,035 |
| 18 | 1 | 4 | 8 | 0,576 | 0,685 | 2 | 1 | 3 | 3 | 4 | 1,000 | 2 | 7 | 46,575 | 4,162 |
| 20 | 2 | 4 | 10 | 0,607 | 0,626 | 5 | 1 | 2 | 3 | 6 | 0,667 | 7 | 9 | -3,865 | 2,202 |
| 22 | 4 | 5 | 12 | 0,717 | 0,616 | 5 | 0 | 1 | 3 | 7 | 0,925 | 13 | 13 | 69,454 | 2,959 |
| 25 | 3 | 9 | 12 | 0,635 | 0,721 | 7 | 1 | 2 | 7 | 3 | 0,638 | 10 | 12 | -2,188 | 5,854 |
| 26 | 3 | 4 | 19 | 0,747 | 0,725 | 6 | 0 | 1 | 3 | 15 | 0,922 | 22 | 19 | 17,263 | 3,743 |
| 30 | 3 | 4 | 9 | 0,726 | 0,761 | 9 | 1 | 1 | 3 | 5 | 0,837 | 16 | 9 | 19,336 | 2,321 |
| 31 | 4 | 5 | 15 | 0,717 | 0,687 | 6 | 0 | 1 | 3 | 10 | 0,871 | 13 | 15 | 39,368 | 0,436 |
| 32 | 4 | 10 | 13 | 0,668 | 0,719 | 6 | 1 | 5 | 4 | 3 | 0,679 | 14 | 13 | 5,282 | 6,904 |
| 32 | 14 | 16 | 19 | 0,663 | 0,773 | 19 | 1 | 5 | 5 | 3 | 0,727 | 1 | 19 | 5,282 | 1,538 |
| 34 | 2 | 3 | 9 | 0,695 | 0,588 | 5 | 0 | 2 | 2 | 6 | 0,837 | 9 | 8 | 87,255 | 0,919 |
| 35 | 2 | 3 | 8 | 0,679 | 0,724 | 3 | 1 | 4 | 2 | 5 | 0,807 | 3 | 7 | 6,848 | 1,321 |
| 36 | 2 | 5 | 11 | 0,701 | 0,761 | 4 | 1 | 2 | 3 | 6 | 0,818 | 5 | 10 | 12,775 | 2,789 |
| 41 | 2 | 4 | 14 | 0,748 | 0,654 | 1 | 0 | 2 | 3 | 10 | 0,976 | 9 | 13 | 11,420 | 2,365 |
| 45 | 3 | 4 | 9 | 0,704 | 0,649 | 5 | 0 | 1 | 3 | 5 | 0,898 | 6 | 8 | 51,055 | 0,210 |
| 46 | 2 | 4 | 9 | 0,626 | 0,531 | 1 | 0 | 3 | 3 | 5 | 0,929 | 3 | 8 | 20,278 | 1,638 |
| 49 | 4 | 4 | 9 | 0,447 | 0,635 | 2 | 1 | 4 | 3 | 5 | 0,923 | 8 | 8 | 41,994 | 1,955 |
| 52 | 8 | 8 | 11 | 0,698 | 0,833 | 10 | 1 | 1 | 4 | 3 | 0,701 | 12 | 11 | 61,404 | 2,419 |
| 53 | 3 | 7 | 11 | 0,813 | 0,670 | 5 | 0 | 2 | 4 | 4 | 0,797 | 10 | 10 | 20,627 | 0,098 |
| 54 | 3 | 1 | 6 | 0,608 | 0,539 | 2 | 0 | 2 | 0 | 5 | 0,735 | 4 | 5 | 21,849 | 6,746 |
| 55 | 2 | 3 | 9 | 0,660 | 0,662 | 3 | 1 | 2 | 2 | 6 | 0,814 | 9 | 8 | -19,459 | 2,747 |
| 58 | 9 | 8 | 12 | 0,672 | 0,691 | 11 | 1 | 1 | 4 | 4 | 0,737 | 12 | 12 | 26,455 | 0,806 |
| 60 | 2 | 5 | 16 | 0,786 | 0,754 | 3 | 0 | 1 | 3 | 11 | 0,905 | 13 | 17 | 5,424 | 1,533 |
| 62 | 4 | 7 | 12 | 0,622 | 0,547 | 3 | 0 | 1 | 5 | 5 | 0,659 | 8 | 12 | 0,819 | 4,425 |
| 65 | 4 | 3 | 6 | 0,628 | 0,677 | 2 | 1 | 2 | 2 | 3 | 0,617 | 6 | 7 | 6,033 | 3,715 |
| 66 | 2 | 4 | 7 | 0,846 | 0,786 | 3 | 0 | 3 | 3 | 3 | 0,986 | 4 | 6 | 13,720 | 0,602 |
| 68 | 3 | 15 | 22 | 0,651 | 0,682 | 16 | 1 | 1 | 11 | 7 | 0,847 | 21 | 21 | 12,689 | 4,994 |

| SIM | ID_ST | TST | TFST | FIT_ST | FIT_BAT | ID_BAT | FST_FB1 | FST | VST | DST | PST | ID_TRET | TR | DCO | DCD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 70 | 4 | 6 | 10 | 0,680 | 0,622 | 5 | 0 | 3 | 3 | 4 | 0,752 | 10 | 10 | 46,450 | 6,625 |
| 71 | 2 | 10 | 28 | 0,554 | 0,738 | 6 | 1 | 2 | 9 | 18 | 0,656 | 24 | 31 | -23,571 | 2,387 |
| 72 | 2 | 4 | 11 | 0,657 | 0,695 | 4 | 1 | 2 | 3 | 7 | 0,928 | 6 | 10 | 40,860 | 2,030 |
| 74 | 2 | 4 | 13 | 0,751 | 0,641 | 4 | 0 | 2 | 3 | 9 | 0,945 | 7 | 13 | 8,857 | 5,524 |
| 75 | 3 | 4 | 11 | 0,819 | 0,764 | 6 | 0 | 2 | 3 | 7 | 0,917 | 13 | 10 | 130,657 | 3,408 |
| 76 | 3 | 3 | 7 | 0,566 | 0,522 | 1 | 0 | 1 | 2 | 4 | 0,574 | 6 | 7 | -17,671 | 0,363 |
| 77 | 2 | 3 | 6 | 0,630 | 0,828 | 4 | 1 | 2 | 2 | 3 | 0,667 | 4 | 6 | 16,443 | 0,970 |
| 81 | 2 | 8 | 11 | 0,648 | 0,697 | 8 | 1 | 1 | 6 | 3 | 0,568 | 3 | 10 | -8,824 | 8,004 |
| 85 | 1 | 4 | 8 | 0,623 | 0,537 | 2 | 0 | 2 | 3 | 4 | 0,745 | 4 | 7 | 5,982 | 2,645 |
| 87 | 2 | 4 | 15 | 0,655 | 0,489 | 1 | 0 | 2 | 2 | 11 | 0,883 | 8 | 15 | 10,751 | 3,546 |
| 88 | 5 | 7 | 10 | 0,657 | 0,682 | 3 | 1 | 1 | 6 | 3 | 0,853 | 8 | 10 | 4,455 | 5,038 |
| 90 | 2 | 2 | 25 | 0,753 | 0,735 | 1 | 0 | 2 | 1 | 23 | 0,647 | 1 | 25 | -4,323 | 8,656 |
| 99 | 3 | 3 | 8 | 0,815 | 0,683 | 5 | 0 | 1 | 2 | 5 | 0,826 | 6 | 8 | 109,492 | 3,465 |
| 100 | 2 | 3 | 7 | 0,658 | 0,641 | 1 | 0 | 1 | 2 | 4 | 0,914 | 4 | 7 | 107,583 | 5,249 |
| 101 | 1 | 4 | 8 | 0,581 | 0,624 | 2 | 1 | 3 | 3 | 4 | 0,897 | 2 | 7 | -0,567 | 1,866 |
| 102 | 2 | 4 | 11 | 0,736 | 0,745 | 3 | 1 | 1 | 3 | 7 | 0,928 | 8 | 12 | 84,478 | 0,966 |
| 105 | 4 | 8 | 12 | 0,734 | 0,741 | 9 | 1 | 1 | 4 | 4 | 0,699 | 12 | 12 | 31,504 | 3,319 |
| 106 | 1 | 4 | 7 | 0,680 | 0,752 | 2 | 1 | 2 | 3 | 3 | 0,833 | 2 | 6 | 2,380 | 2,418 |
| 109 | 9 | 10 | 13 | 0,580 | 0,622 | 4 | 1 | 1 | 4 | 3 | 0,707 | 11 | 13 | 46,684 | 2,310 |
| 114 | 11 | 10 | 13 | 0,638 | 0,735 | 10 | 1 | 1 | 4 | 3 | 0,575 | 16 | 19 | -19,264 | 0,083 |
| 115 | 3 | 6 | 12 | 0,717 | 0,830 | 5 | 1 | 2 | 4 | 6 | 0,910 | 11 | 11 | 30,238 | 3,597 |
| 120 | 3 | 4 | 19 | 0,747 | 0,725 | 6 | 0 | 1 | 3 | 15 | 0,922 | 22 | 19 | 17,263 | 3,743 |
| 121 | 5 | 7 | 10 | 0,619 | 0,733 | 7 | 1 | 1 | 6 | 3 | 0,600 | 7 | 9 | 4,143 | 3,941 |
| 126 | 4 | 4 | 8 | 0,638 | 0,612 | 3 | 0 | 2 | 3 | 4 | 0,671 | 8 | 8 | 66,036 | 1,554 |
| 128 | 2 | 4 | 10 | 0,702 | 0,664 | 5 | 0 | 2 | 3 | 6 | 0,813 | 11 | 9 | 28,221 | 1,091 |
| 132 | 2 | 5 | 9 | 0,771 | 0,631 | 7 | 0 | 2 | 4 | 4 | 0,789 | 11 | 10 | 58,527 | 4,515 |
| 133 | 1 | 4 | 7 | 0,559 | 0,668 | 2 | 1 | 3 | 3 | 3 | 1,000 | 2 | 6 | 22,446 | 0,380 |
| 136 | 3 | 7 | 10 | 0,751 | 0,782 | 2 | 1 | 2 | 4 | 3 | 0,750 | 1 | 9 | 8,860 | 4,980 |
| 137 | 2 | 2 | 8 | 0,687 | 0,694 | 3 | 1 | 2 | 1 | 6 | 0,831 | 7 | 8 | -7,965 | 2,964 |
| 140 | 2 | 5 | 10 | 0,676 | 0,733 | 5 | 1 | 1 | 4 | 5 | 0,679 | 4 | 10 | 69,611 | 8,182 |
| 141 | 2 | 7 | 11 | 0,756 | 0,669 | 3 | 0 | 2 | 6 | 4 | 0,753 | 3 | 11 | 35,131 | 1,998 |
| 142 | 3 | 5 | 8 | 0,756 | 0,743 | 7 | 0 | 3 | 4 | 3 | 0,651 | 6 | 7 | 3,273 | 0,394 |
| 144 | 1 | 4 | 8 | 0,590 | 0,921 | 5 | 1 | 1 | 3 | 4 | 0,844 | 2 | 26 | -1,299 | 1,951 |
| 146 | 3 | 5 | 14 | 0,716 | 0,734 | 5 | 1 | 2 | 3 | 9 | 0,875 | 12 | 13 | 67,962 | 1,493 |
| 147 | 2 | 4 | 10 | 0,730 | 0,568 | 3 | 0 | 2 | 2 | 6 | 0,966 | 7 | 10 | 74,271 | 2,691 |
| 148 | 1 | 3 | 6 | 0,592 | 0,557 | 2 | 0 | 2 | 2 | 3 | 0,582 | 5 | 7 | 0,580 | 6,149 |
| 150 | 16 | 14 | 18 | 0,493 | 0,693 | 9 | 1 | 1 | 2 | 4 | 0,838 | 19 | 19 | -18,174 | 9,669 |

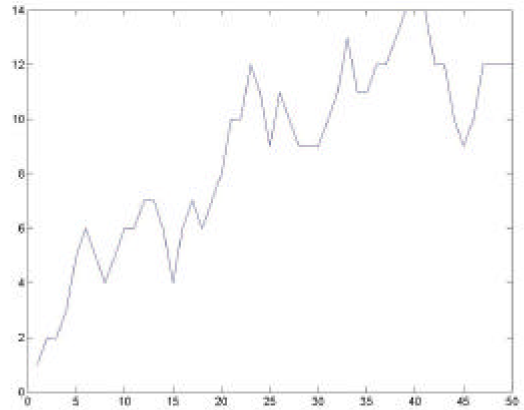
Appendix 3. Graphical results of a typical model simulation using the base scenario




*Evolution of technologies adoption*
*(market shares / time)*

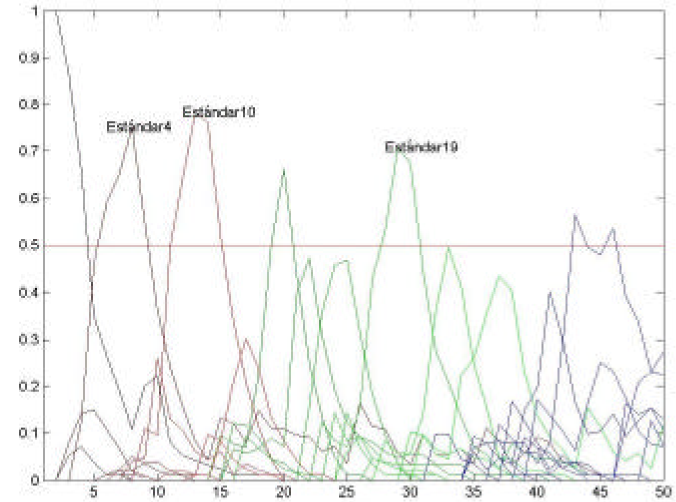



*Evolution of the population of firms*
*(number / time)*

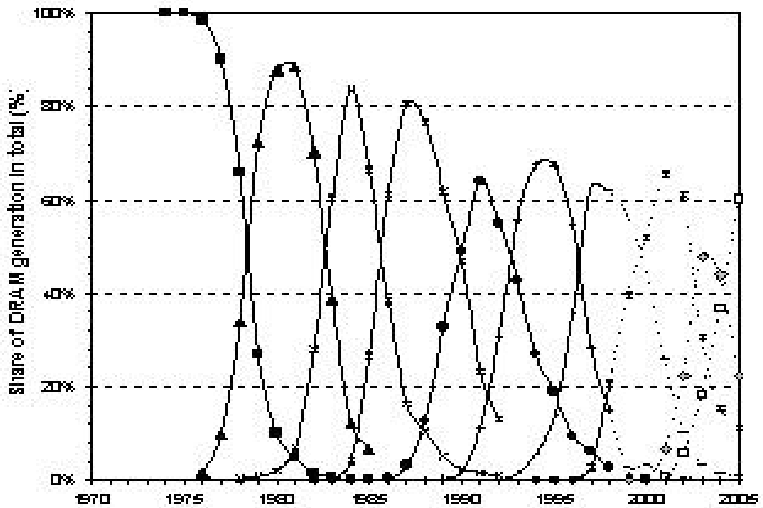



*Evolution of the population of technologies*
*(number / time)*

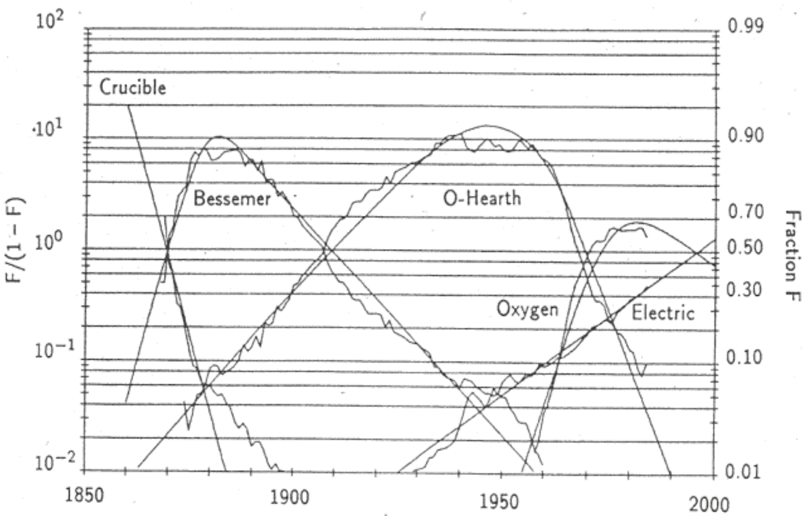
Appendix 4. Visual isomorphism between the results of the model and the patterns of the phenomenon observed in real industries



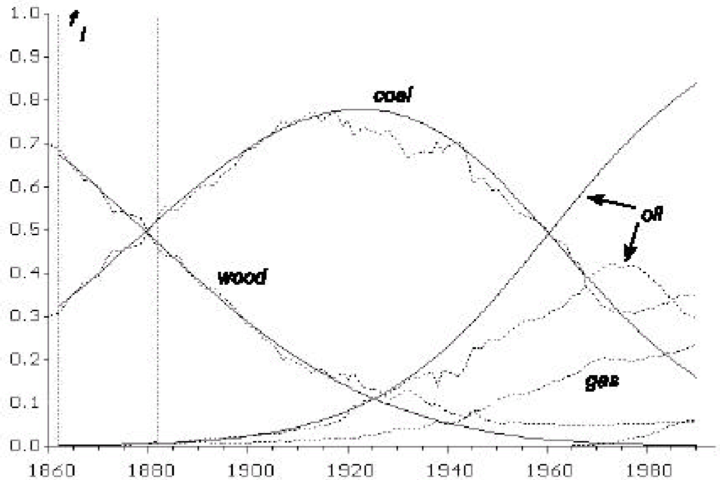

*Typical results of the model (base scenario)*




*RAM technologies (Nadejda y Ausubel, 2002)*




*Steel manufacturing technologies (Grübler, 1991)*




*Power generation technologies (Kwasnicki, 1999)*

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