Pergamon

PII: S0166-4972(98)00021-2

Technovation, 18(6/7) (1998) 439–457

Printed in Great Britain
0166-4972/98 $19.00 + 0.00

Performance analysis of technology using the S curve model: the case of digital signal processing (DSP) technologies

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Abstract

The purpose of this paper is to analyse the evolution of the technology performance of Digital Signal Processing components (DSPs) using the S curve model. In the first part, the theoretical base of this model is established through a comparative study between the S curve model and other concepts with which it is closely related: innovation diffusion models and life cycle models. The purpose of this study is to use the solid analytical foundation of these models to increase the theoretical consistency of the S curve model. In the second part of the article, a methodology that facilitates the application of this model is proposed. At the same time, the usefulness of the S curve as a strategic analysis tool is discussed as well as the problems that can arise when the model is put into practice. This methodology is used in the analysis of the technology of DSPs. © 1998 Elsevier Science Ltd. All rights reserved

1. INTRODUCTION

The progressive acceleration that technological changes have experienced in recent decades has demonstrated the need to consider the incidence of such technological advances in all areas of enterprise. It has been demonstrated that technology determines, to a large extent, the competition level, and the need to incorporate technological analyses in the process of formulating strategies has been emphasized. In the

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literature of technology management, numerous methodologies that facilitate the link between technology and strategy have been proposed. One model that has been widely published, is the so-called S curve, which enables the analysis of the evolution of the performance of any technology. The majority of manuals about the strategic management of technology (Betz, 1993; Dussauge *et al*., 1992; Goodman and Lawless, 1994; Twiss, 1986) use this model and suggest its use to make predictions about the evolution of the rate of technological change, to detect possible technological ruptures, or to determine the limits of a particular technology.

In the first part of this paper, the model of the S curve is examined by establishing links with other similar concepts with which it is closely related. Traditional separation, existent in the fields of economy and management, has brought about a proliferation of equivalent concepts and has consolidated methodological differences that undoubtedly impede or obstruct terminological normalization and the transmission of knowledge. This fact justifies the need (before presenting the empirical work in the following section) to reflect upon the existing relationships between the concept of the S curve and other diffusion of innovations models (used in the fields of industrial economy and marketing) and life cycle models (used in the literature of strategy, production and marketing).

In the second part, the technology performance of digital signal processors (DSPs) is analyzed by means of the S curve model. DSPs constitute a new family of semiconductors that have numerous applications in the scope of information and communication technologies (ICTs). DSP components will become a major growth area in the semiconductor components market over the next few years (Price Waterhouse, 1994). The S curve model will allow evolution of the technology performance of DSPs to take place as well as estimate the limits of its growth potential. This analysis is achieved by following an original methodology which enables it to overcome the problems that may appear when this model is put into practice. In addition, the possibilities of the S curve model as a strategic analysis tool and its usefulness in the design of strategic technologies will be discussed.

2. THEORETICAL FOUNDATIONS OF THE S CURVE MODEL

Before presenting the results of the analysis of the technology performance of DSPs using the S curve model, it is important to reflect upon its theoretical foundations. In spite of the fact that the S curve model has been studied extensively in recent years, especially since the publication of Foster's book (Foster, 1986a), there are no studies that establish the basis of its theoretical foundation. The primary objective of this paper is to make every attempt to increase the theoretical consistency of this concept using the solid theoretical and empirical groundwork of other models (which appear in the field of economy and management) to which it is related. It seems appropriate to analyze its antecedents before exposing the main characteristics of this model. Therefore, two model families that are closely related to the concept of the S curve are identified below:

(1) diffusion models, and
(2) life cycle models.

Diffusion models attempt to analyse the process by which an innovation is diffused throughout a determined social system (Rogers, 1993). Most of the research regarding diffusion processes has been carried out by scholars from the field of industrial economy and marketing. Therefore, in these models, variables that are related to the structure of the industrial market in which the innovation is diffused and other characteristics of the overall economic environment play a relevant role. The first studies that were carried out in the 1960s and 1970s were concerned primarily with predicting the diffusion speed of the innovations. In general, the models that were proposed were quite rigid and incorporated very restrictive hypotheses: innovations with constant technology performances over time, constant market potentials, etc. During the 1980s and 1990s, new models have appeared. They reduce these hypotheses and include new explicatory variables: price, advertising, etc. These recent studies (Mahajan *et al*., 1993) emphasize the role of diffusion models as analysis instruments to formulate strategies.

The life cycle models have been used in different management fields (strategy, marketing, production) in order to represent the evolution of industries, products, brands, etc. The most widespread among them is the one that describes the different stages in the temporal evolution of the sales of a product. Using the conceptual framework of the life cycle model, some authors have defined different models that are representative of the evolutions of technologies (Abernathy and Utterback, 1975; Ford and Ryan, 1981; Roussel *et al*., 1991). These models assume that the life cycles of technologies, industries and products follow similar patterns to that of the biological cycle of living beings and therefore are easily predictable.

Because the S curve model represents the evolution of technology performance, it is as clearly related to diffusion models as it is to life cycle models. Its capacity to analyze technological performance potential makes this model a useful tool for designing technological strategies. However, like many other models that are developed in the management field, its limited analytical base diminishes its theoretical consistency. This fact makes it difficult to achieve empirical contrasts and their application in the analysis of concrete cases. Continuing with what constitutes the first part of this paper, existing relationships between diffusion models and life cycle and S curve models will be analyzed. This analysis will clearly demonstrate the common link between these models and the S curve. In addition, it allows for the demarcation of the theoretical foundations of the S curve model, increasing its consistency by using the solid analytical base of the diffusion and life cycle models.

2.1 Diffusion models

Studies of technological change, attained under the perspective of industrial economy, have paid special attention to the processes of innovation diffusion. In large part, these works (Baldwin and Scott, 1987; Davies *et al.*, 1991; Stoneman, 1983, 1995) gather and synthesize different analytical models that describe the evolution patterns of existing technologies and their substitution for newer ones, both in products as well as processes. In general, these analyses have centered on the speed of diffusion of the technologies in different sectors, and they have tried to identify the factors that determine it.

Kuznets (1930) was among the first to recognize that technological change was able to evolve by following the known model of the S curve. Subsequently, the highly revealing research of Griliches (1957) on the diffusion of hybrid corn seeds in different geographical areas of the United States, and of Mansfield (1961) on the diffusion of 12 technologies among the largest enterprises of four sectors (bituminous coal, iron and steel, beer, and railroads) confirm this regularity in the diffusion process of new technologies.

Mansfield (1961) suggests that the representation of the temporal evolution of firms that have adopted a technology in an industry approaches logistical growth function, known as Pearl's law (Pearl, 1925). This function is symmetrical and in the shape of a positive S gradient. This is a growth function which is frequently used in biology and social sciences to supply models for every kind of diffusion process (epidemics, rumors, etc.). The underlying hypothesis in diffusion models that are based on the logistical function is very simple: the speed to which the total number of firms that adopt a new technology increases, depends on the number of firms that have already assimilated it and the potential number of firms that have not yet incorporated it. Intuitively, this same idea can be expressed in epidemiological terms: 'the speed with which a contagious disease is spread is directly proportional to the number of people infected to date and the size of the city that is potentially exposed to the disease'.

Mansfield, after a series of manipulations and approximations, transformed the function into a usable expression:

$$m_{ij}(t) = n_{ij}[1 + \exp\{-(l_{ij} + \varphi_{ij}t)\}]^{-1}$$

where:

$m_{ij}(t)$	number of firms that have introduced innovation up to the instant t
n_{ij}	total number of firms
l_{ij}	integration constant
$\varphi_{ij}t$	rate of imitation

The form of this function will depend solely on the parameter $\varphi_{ij}t$ that represents the *rate of imitation* which, in accordance with the adopted hypotheses, is a lineal function of: (1) the profitability of the installation: π_{ij}; (2) the investment volume required for its installation: S_{ij}; and (3) the contingent variable with an expected null value that obtains the effect of other non-specified variables: z_{ij}.

$$\varphi_{ij}t = a_{i1} + a_{i2}\pi_{ij} + a_{i3}S_{ij} + z_{ij}$$

In this representation of the diffusion process of a technology in an industry (Fig. 1), there are three clearly defined phases:

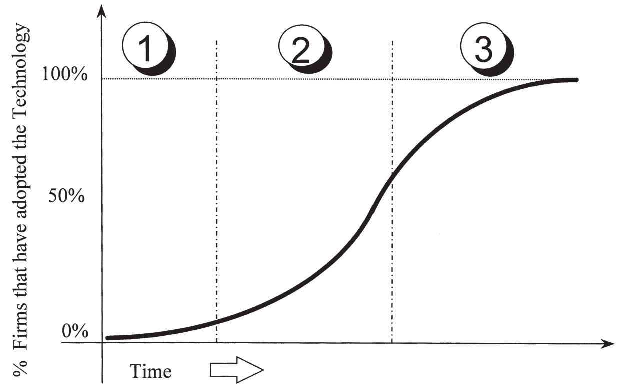

Fig. 1. Diffusion model.

(1) There is great uncertainty in the results and the investment is risky. The number of firms that incorporate the new technology is reduced. The diffusion process is slow. The learning process begins and the rate of technological performance innovation increases slowly.
(2) In the course of time the technology demonstrates its utility and achieves success. The diffusion process accelerates. The accumulated understanding accelerates the increments in technological performance.
(3) As long as the proportion of firms that have not adopted it is less and/or the ones that lag behind opt for another new technology, the speed of diffusion is reduced. The technology approximates its performance limit and its productivity diminishes.

Since Mansfield's research, countless empirical works have been offered. In them, other functional expressions of logistical growth function are suggested. Fisher and Pry (1971) employ a hyperbolic tangent function to analyze the substitution process of technologies that were competing in the same industry. Lal *et al*. (1988) proposed a model in differential terms that takes into consideration the time interval that the innovative potential uses to study and adopt new technology. Meade (1989) and Oliver and Yang (1988) suggest that the diffusion process be analyzed in terms of probability by incorporating the likelihood of market deciders adopting the new technology.

This logistical growth function has been utilized profusely in the modeling of diverse diffusion processes of new product technologies/processes in different markets/industries: tractors and agricultural machinery (Oliver, 1981); household appliances and color televisions (Meade, 1988); industrial robots (Mansfield, 1989); new telecommunication technologies (Campisi and Tesauro, 1992); and oxigen-steel technology (Kumar and Kumar, 1992). Nonetheless, some works have indicated that this model, which uses the diffusion of information or epidemics by contact as a paradigm, is analytically inadequate for examining the diffusion of innovations, since there are radical differences in the nature of these processes. Thus, it has been indicated that the static nature of the diffusion model does not allow for increasing improvements in the performance of different technologies (Metcalfe, 1981); nor does it establish, when considering each technology separately, interrelations between the diffusion of different technologies that are integrated into the same technological system (Freeman *et al*., 1982).

In addition, diffusion of and access to information about the characteristics of a new technology is only the first step in a complex, decision-making process that will conclude with its incorporation into the firm. These criticisms seem to give direction to the search for factors which determine the diffusion speed of innovations towards other scopes that are closer to the process of making decisions at enterprise level. It will be necessary to describe the mechanisms that determine the diffusion of a technology, by relating them to their capacity to generate new products and/or create new markets; a capacity that, as a last resort, will be determined by its technical performance.

Along the same lines, some studies have considered explicatory variables that reflect certain characteristics of the adopting firms and the nature of the technology. Therefore, using the ideas proposed by Rogers (1993), Bass (1969) developed logistical model that could reflect different strategic behaviors of the agents. Bass distinguishes the innovative firms which, at the beginning of the process adopt the innovation autonomously, from the imitative firms which little by little incorporate it after becoming influenced by the contagion of the innovators. The logistical function has also been employed by Mansfield (1968) to analyze the intra-firm diffusion process. In this model Mansfield incorporates a series of commercial (size and cash-flow) and technological (performance and risk associated with the adoption of a new technology) variables that are not ordinarily gathered in the inter-firms diffusion models. Davies (1979) has pointed out that size is the commercial variable that has greatest explicatory power, as it is usually correlated to other commercial variables such as: (1) learning capacity to acquire and assimilate new technologies; (2) attitude towards risk; and (3) long-term objectives of the firm.

Nonetheless, the majority of the research recognizes that the diffusion of innovation technologies evolves by following average behavior patterns (identifiable by means of sinusoidal functions) similar to the one described by the S curve. The diffusion models are useful for studying the process of technological change on a macro-level. On the contrary, its applications in the field of management are limited. At a commercial level, it is more important to model the evolution of the technological performance of a specific innovation than to know the speed of diffusion.

Similarly, in the literature pertaining to management other concepts, closely related to diffusion models, have come forth: life cycle models. These models have a fundamentally practical orientation. They are analysis tools that help the adoption of strategic decisions. In the following section, their principal characteristics will be described, as we point out their similarities with the S curve model.

2.2 Life cycle concept

In different works in the field of management, the term life cycle has been used to describe some generic models. These models represent the evolution of industrial sectors, products, technologies, etc. The most widespread among them, initially formulated by Levitt (1965), is the one that refers to the life cycle of a product and describes the evolution of the volume of sales over time.

Just as in the biological cycle of living beings, in the life of a product, four stages can also be distinguished: introduction, growth, maturity and decline (Fig. 2). Some research (Cox, 1967; Swan and Rink, 1982; Tellis and Crawford, 1981) has demonstrated that not all products go through a vital theoretical cycle that is represented in the form of an S. However, numerous empirical studies have contrasted the validity of the model that adapts itself to a logistic function in its first three stages:

(1) Introduction: a new product is introduced into the marketplace. Only one or two firms have entered the market, and the competition is limited. The rate of sales growth depends on the newness of the product. Generally, a product modification generates faster sales than a major innovation. The technology performance of the innovation increases slowly.
(2) Growth: a new product gains wider consumer acceptance and the objective is to expand the range of available product alternatives. Industry sales increase rapidly as a few more firms enter the marketplace. To accommodate the growing market, modified versions of basic models are offered. Successive incremental innovations increase the technology performance rate of the product.
(3) Maturity: industry sales stabilize as the market becomes saturated and many firms enter to capitalize on the still sizable demand. The possibilities of increasing product contributions are limited. Innovations are less frequent. The technology performance rate stabilizes.

It has been recognized that these models are based on the theory of diffusion and adoption of innovations (Ansoff, 1984; Kotler, 1994) and that they are considered to be conceptually derived from the diffusion models that were described previously. In large part they complement the diffusion models in that, while these models enable us to predict the speed of technological changes, life cycle models reveal their impact on markets and products (Betz, 1993).

One problem that has traditionally been associated with the use of these models is the definition of unit analysis. Thus, depending on how branded products, product forms, product categories or industries are treated, different life cycles can be developed. The process of diffusing innovations is underlying all of these models. However, the intensity of the relation may vary depending upon which analysis unit is chosen.

The technological factor affects the product forms and brands to a lesser degree than the product categories. The effects of fashion and other commercial variables become watered down by the similarities within the total offering of manufacturers (product category). The duration of the different stages and the total life of the product depend on factors of a technological nature. When the diffusion speed of new technologies is increased, product performance improves and/or the efficiency of the processes increases. In Fig. 3 the

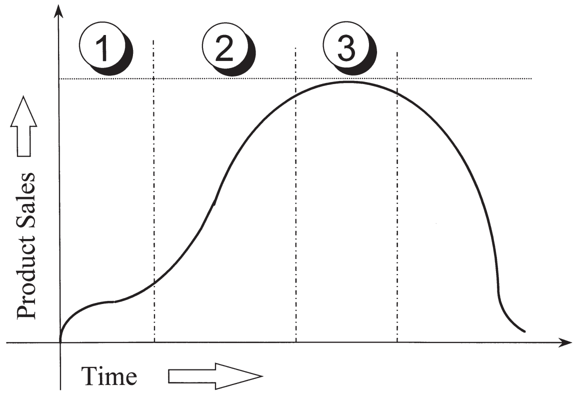

Fig. 2. Product life cycle model.

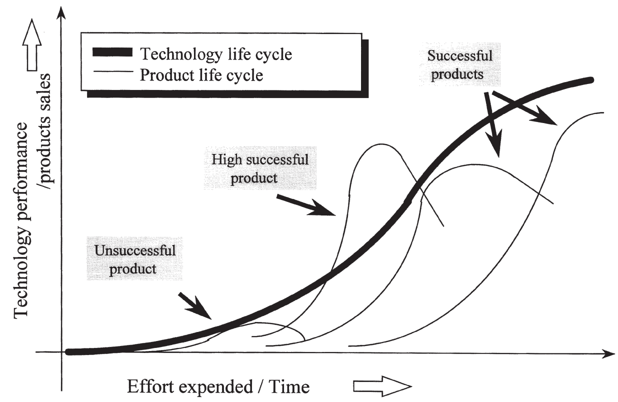

Fig. 3. Relationship between the technology life cycle and life cycles of products.

existing relationship between the life cycles of the technology and that of the products is shown.

The life cycle model at the industry level has been used profusely in the field of strategic management. Porter (1980) characterizes the evolution of an industrial sector by using the curve in the shape of an S with which he distinguishes four defined stages by the inflection points on the growth rate of total sales. Although this model acceptably describes the evolution of the majority of sectors, Porter recognizes its limitations, and therefore, suggests that it is necessary to consider all of the forces that condition the life cycle of the sectors. These forces, known as evolutionary processes, are of a dynamic nature and differ when they are in divergent sectors. Of the evolutionary processes analyzed by Porter (1980), at least four have a clear technological component: diffusion of patented knowledge, accumulation of experience, product innovation and process innovation.

Therefore, the link between technology and life cycle at the industrial level seems far narrower than at product or brand levels. Thus, the appearance of new technologies in many cases can create the emergence of new sectors or the revitalization of already existing ones. In addition, the maturity and decline of old technologies can induce the restructuring of some sectors, and in extreme cases, cause their disappearance (Dussauge *et al*., 1992). Keeping in mind that the life cycle of technology and the life cycle of sector often reveal the same phenomenon, some authors do not differentiate and integrate them into what has been named industrial technology life cycle.

Although life cycle models may represent the most frequent standard of product and industrial evolution, some conceptual inconsistencies have been pointed out. The two most significant objections are: (1) their quasi-tautologic nature (sales define the phases of the product life cycle that, at the same time, explain the sales); and (2) their large determinist component (it tries to describe a pattern of evolution that will invariably occur) (Porter, 1980). According to this, the explanatory and predictive capacity of these models is limited in so far as they do not incorporate variables that determine the evolution of the cycle.

2.3 Technology life cycle and the S curve model

It has been noted that the concepts of sector life cycle and technology life cycle are, in practice, closely related, as technological changes determine, to a great extent, the evolution of the industry. However, some authors have proposed life cycle models that differentiate between technology and industry.

Since Abernathy and Utterback's research (1975) about the evolution of product and process technologies, Ford and Ryan (1981) have defined the concept of technology life cycle. They propose a conceptual standard that allows the base level of technological development to the application level of different technologies to be revealed. With this finding, they claim to guide the adoption of strategic decisions, particularly as far as the sale of technology is concerned.

The consulting firm Arthur D. Little (1981) has developed a technological life cycle model that represents the evolution of the technologies with a system that is similar to the one used to reveal the life cycle of an industry, but it utilizes, on the vertical axis, some qualitative measure of technological advancement. However, some of their consultants (Roussel, 1984) have recognized the need to quantitatively express the concept of technological performance, as both upper management and engineers request more concrete data. According to its developmental phase (or technological maturity), the technologies are described as embryonic, growth, mature and aging (Roussel *et al*., 1991). Since this classification, there tend to be recommendations for the strategic management of technology.

Another way of creating a technology life cycle model which may resolve this problem is by using the S curve model. This is a function that relates the accomplished effort in the development of a technology with the results that are obtained. It is called S curve because, when the results are graphically demonstrated, the curve that is usually obtained is a sinusoidal line that resembles an S (Fig. 4). This function is similar to the one used in models of innovation diffusion. This model, initially conceived by Richard Foster (1986a), director of the consulting firm McKinsey, has received widespread acclaim in the field of technology management.

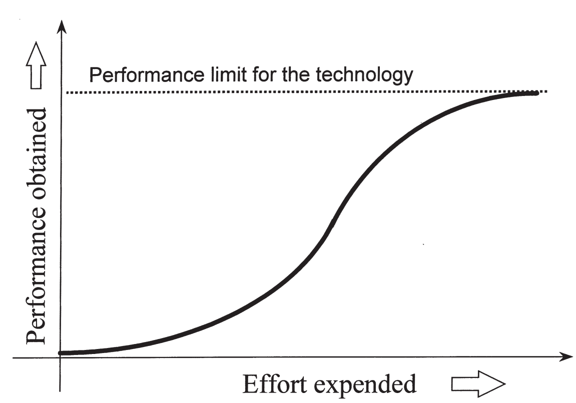

Fig. 4. The S curve model.

Consistency and similarity between the different phases of the S curve and the characterization of the stages in the life cycle of a technology in previous models are evident. In Fig. 5 the close relationship between the technological categories, as proposed in Arthur D. Little's model, and the S curve are indicated. Furthermore, the objective of these models is the same: to verify the rationality of technological strategies. In fact, by means of these models a firm can know the situation in which a specific technology is found at a particular point in time, as well as foresee its future evolution and its developmental limits.

There is a great deal of empirical evidence that the S curve reveals the general evolution process of the performance of technologies and that this finding systematically repeats itself in all industrial sectors. In addition to the original works of Foster (1982a, b, 1986a, b, c) other authors have developed theories with effective data. Becker and Speltz (1983, 1986) have proved that the technological performances of insecticides for agricultural use evolve in accordance with patterns that are defined by the S curve. Lee and Nakicenovic (1988) have analyzed substitution phenomena among different technologies as they are employed in the transportation sector (air, railway) and in the energy sector (gas, petroleum, electricity). Roussel (1984) has used the S curve to study derived plastics and their application to the automobile industry.

Foster (1986a) pointed out that the progress of a new technology must never be represented in terms of time, but rather in terms of the actual investment in its development (measured in monetary units, number of researchers, hours worked, workers per year, etc.). If, on the contrary, it were represented in terms of time, no extrapolation could be carried out because in the diagram, implicit assumptions about applied force would remain hidden. In this way, if the rate of investments changed, the time necessary for the performance of the technology to improve would increase or decrease. Nonetheless, the difficulties associated with obtaining data about the investment that is made by different firms in the development of a specific technology are often irreparable. Consequently, many empirical studies (Roussel, 1984; Becker and Speltz, 1983, 1986; Lee and Nakicenovic, 1988) have modeled the technology performances according to the time.

On the other hand, the parameter of the global performance value of a technology can be created upon establishing a carefully measured sum of different elements that reveal technical aspects as well as commercial ones. That is to say, two requirements should be met (Foster, 1986a, b, c): 'It should express something valuable for the client, and it should do so in terms that make sense to the scientists and engineers of the company'. If the performance parameter is defined in a way that acceptably reflects all the technological improvements that may affect the contribution (quality, safety and cost of the products), the S curve model would facilitate the understanding of the process of technological change. In this way, when the S curve is used as a performance model of evolution of a specific technology, what it is demonstrating in reality is the speed at which incremental innovations in a given technology are produced. Therefore, if the performance parameter is defined adequately, the S curve model would provide reliable analyses from which significant recommendations for the design of technological strategies could be derived.

The gradient of any point of the curve reveals the productivity of the investments in R&D (Fig. 6). On

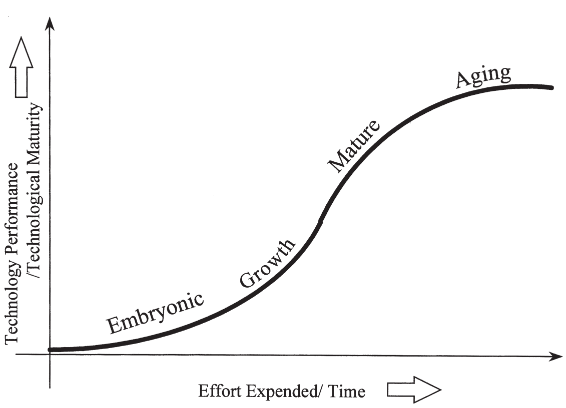

Fig. 5. Technological maturity and the S curve model.

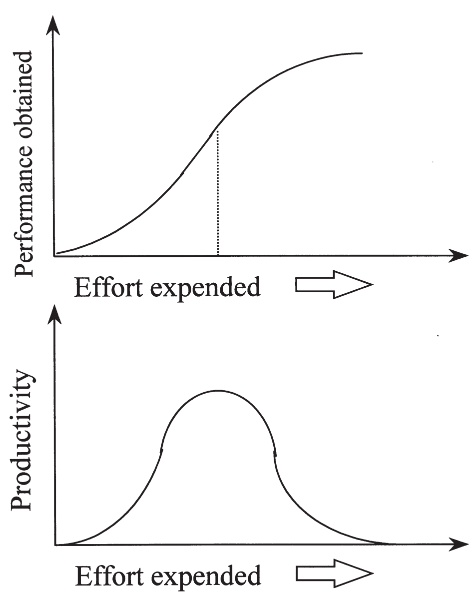

Fig. 6. S curve and R&D productivity.

the upper half of the S curve, past the point of inflection, the productivity of R&D is decreasing. From that point on, the productivity of technological investments will only increase by abandoning the present technology to adopt a new one. It is at that moment when it is most difficult to make this decision, as the technology is at its maximum performance and there is little reason to risk investing in new technologies (Becker and Speltz, 1986). Likewise, it has been pointed out that company management tends to underestimate the speed with which the progress of a technology takes place when it is found in the middle of the exponential growth phase (Twiss, 1986).

Representing the S curve of two or more alternating technologies can be especially revealing. On many occasions there are different technologies which compete amongst themselves, each one with its own S curve. When one of them successfully imposes itself on another, a discontinuity appears: a rupture in the S curve is produced and a new one is now formed. Identifying a discontinuity at the moment in which the facts are being produced can be very difficult, but extremely useful.

Gathering all the information that is necessary to construct an S curve requires time and can be costly. Foster (1986a, b, c) recommends constructing the curve only in those cases in which there are marked differences of opinion about which strategy to choose. In these cases, the value of the response can compensate for the cost of gathering information. In other cases, creating a collection of S curves that may reveal different parameters of one technology can be more useful than a single S curve (Lee and Nakicenovic, 1988).

In addition, the S curve can be used in making predictions. In fact, if it is possible to define reliable performance parameters, relating the early advances of these parameters to the realized investment and estimating what their limits are, a basis for evaluating to what extent current technologies may improve and at what cost will be established. Likewise, when a company foresees that a technology is near its performance limit, it will no longer invest in it, as only small improvements will be achieved in exchange for costly investments.

In general, the firm bases its strategic decisions regarding the adoption of innovations in products/processes on analysis and foresight of the performance of the technologies that they incorporate. The S curve model and life cycle models of technology can, in general, be useful in designing strategies, since they allow for the analysis and foresight of performance potential of technologies. However, it is necessary to keep in mind that the S curve model is a typical product of consultation. It was conceived exclusively as a practical tool and therefore presents certain inadequacies of a theoretical nature. This limited theoretical base makes its application in the analysis of concrete cases rather difficult.

As a theoretical conclusion, the existing links between the previously described models are emphasized. On the one hand, the similarity between analytical expressions that are used is evident: logistical functions, Gompertz curve, etc. On the other hand, they all attempt to model some aspect of the process of technological change. Some emphasize the evolution of the performance technology, others the diffusion process or the effects on life cycle products and industries. With these conclusions, our intention is to use the solid theoretical and analytical foundation and the diffusion models of innovation to increase the theoretical consistency to the S curve model and justify the methodology that is employed in the empirical studies.

2.4 Relations between the three types of models

These three types of models come from different studies and strive to use different phenomena as models. Among them, it is possible to establish distinct hierarchies in terms of their generality level, their stage of formulation and their explicative capacity (Table 1). However, among them it is possible to detect certain similarities. These originate in the common bond that connects all of these concepts: the technological factor.

In the field of industrial economy, models that allow the analysis of the diffusion of innovations at a sectorial level have been proposed. The diffusion speed of a technology will depend on the proportion of companies that have already adopted it, the required investment volume, its profitability, the degree of market concentration, the size of enterprises that do business in the sector, etc. These models are useful at an additional level for making decisions about the design of industrial and technological policies. However, they do not describe the nature of the decision-making mechanism that induces the diffusion of innovations at firm level: increase of investment in R&D in terms of the expectations of technological performance increase.

Life cycle models describe the evolution of products and/or markets at different levels (industry, product, brand). Emerging from studies in the fields of marketing and strategy, they have been employed

TABLE 1. Comparison of models

Model	Phenomenon analyzed	Analysis unit	Main field	Origin
Diffusion	Diffusion and substitution process of a technology over time	Economic system Industry	History of technical change Industrial economy Marketing	Griliches (1957); Mansfield (1961); Fisher and Pry (1971)
Product life cycle	Evolution of sales of products based on the same technology over time	Firm Business unit	Marketing Strategic management	Levitt (1965)
Industry life cycle	Effects that the technological change has on the production volume of an industry over time	Industry	Industrial economy Strategic management	Porter (1980)
Technology life cycle	Effects that the evolution of the technology has on the firm strategy	FirmBusiness unit	Production management Strategic management Technology management	Abernathy and Utterback (1975); Ford and Ryan (1981); Roussel and Arthur D. Little, Inc. (1981)
S curve	Technology performance over time (or effort expended)	Industry Firm Business unit	Technology management	Foster and McKinsey and Co, Inc. (1986)

intensively in support of strategic decision-making. Although in some cases these models may reveal the effects of technological changes on markets and/or products, they do not provide information about the causes that create them (variations of the performance of the technologies).

Life cycle technologies strive to explain the evolution of technologies in exclusively technological terms. This family of models clearly reveals the evolution of the performances of the technologies. The evolution of the performances of a technology is the variable that explains its speed of diffusion, and that conditions the life cycle of the products/industries that incorporate it. Of all the technological life cycle models, the S curve, which connects the investment of technology with the performances that it generates, is the one that shows a greater usefulness in formulating technological strategies. However, the S curve model does present difficulties of a practical nature in selecting and evaluating the performance parameter and in calculating the total cost of the investment.

In spite of the fact that they come from different areas of study and represent different phenomena, these families of models have a common nexus. On the one hand, the S curve models variations in the performance of a technology based on the effort in R&D which is realized in its development and/or time. On the other hand, the diffusion process of innovations has been modeled as a consequence of the technological performance explicatory variable. Along these lines, Betz (1993) has identified some connections between the technological performance variable and the diffusion process of new technologies:

- If the new technology brings forward a non-existent functional capacity, it will create new markets and its speed of diffusion will depend on the increases in the technical performance that it generates. These increases in performance will contribute to the widening of the markets, by means of new products and/or cost decreases.
- If the new technology does not create a new functional capacity and only substitutes an already existing one, its speed of diffusion will depend on the relationship between performance improvements and costs.
- The speed of diffusion will depend on the character of the new technology, whether it deals with radical innovation followed by increasing improvements, or it deals exclusively with a series of increasing improvements that, through accumulation, provoke a radical change within time.

These three relationships emphasize the role of technology performance as an inductor mechanism of the diffusion process of innovations. This explains why the technological performance variable of a specific technology (modeled by the S curve) follows a behavior pattern which is similar to the one described by the diffusion models of innovations.

Consistent arguments can also be found to relate the life cycles of products/industries to the life cycles of their principal technologies. On the one hand, the evolution of the technological performance of a technology conditions the life of the products that incorporate it. If the increases in technological performance are perceived by the market, they will be translated into increases of volume in sales (Ansoff, 1984). On the other hand, the performances of principal technologies that characterize an industry, determine the life cycle and define the competition. In fact, the transition between the principal phases in the evolution of an industry (birth, development, maturity, decline or revitalization) have been explained according to the performance of their technologies (Porter, 1980).

3. ANALYSIS OF THE TECHNOLOGY OF DSPS

The S curve allows for the evolution model of the performance of any technology. In spite of not being a very precise tool of technological foresight (Lee and Nakicenovic, 1988), the S curve can be very useful in orienting the technological strategies of firms. In fact, this model supplies information: (1) about the magnitude of effort necessary to obtain a determined increase in the productivity of a technology; and (2) about the existence of natural limits in its performance.

The use of the S curve model to analyze a particular technology poses diverse difficulties of a practical nature. The literature has recognized: (1) the difficulty of estimating the parameter of technology performance; and (2) the near impossibility of obtaining reliable information about investment that is made in the development of different technologies. The empirical research that has been published has resolved these problems in different ways. Generally speaking, in these studies the adopted solutions have not been justified in relation to existing scientific literature, nor have they been articulated in an operative methodology.

Having established the theoretical basis of the S curve model, the second part of this paper will be devoted to the problems that arise when putting it into practice. The structure of the operative methodology developed to analyze the technology performance of DSPs will be discussed. This methodology can be outlined in three phases:

(1) selection of the technology to be analyzed;
(2) definition of the technology performance indicator; and
(3) construction of the S curve.

In the following section, the principal problems that arise in each of these phases will be described and possible solutions will be suggested. At the same time, the analysis results of the technology of DSPs will be presented.

3.1 First phase: selection of the technology to be analyzed

Little attention has been given to this phase in most of the empirical research that has been carried out to date. In our opinion, this aspect is critical, as an incorrect selection of the technology to be studied can create errors in the strategic analyses and lead to the formulation of inconsistent technological strategies.

The selection of the technology poses three different problems. In the first place, it is necessary to *identify* the technology in a precise way in order to differentiate it from others that have similar characteristics or that perform the same functions. Secondly, it is necessary to *evaluate* the role of the technology in relation to the technological system in which it is immersed. No technology can be analyzed in an isolated way without taking into account the interactions of other technologies within its technological system (Metcalfe, 1981; Freeman *et al*., 1982). Finally, it is necessary to evaluate the impact of the technology on the present and future activities (products/processes) of the firm. These aspects are closely related and therefore should be analyzed together. In all certainty, if in this first phase a faulty selection of the technology to be analyzed is produced, the S curve model will lead to erroneous and irrelevant conclusions.

The selection of a technology of DSPs was made as a result of two complementary analyses: (1) the identification of the technology to analyze; and (2) the evaluation of its impact on the technological system. On a commercial level, the impact of DSPs on the activities was not evaluated, as this was not an objective of our study. If this analysis had presented itself for a specific firm, the impact of the technology on its activities would have had to be analyzed.

3.1.1 Identification of the technology of DSPs

Identifying a technology consists of differentiating it from others that have similar characteristics or that perform the same functions. In our case, the DSPs are microprocessors which belong to the extensive family of digital devices. The basic function that DSPs perform is to digitally process the signal. As an alternative, the signal can also be processed analogically using other semiconductor components. Therefore, the first step in our analysis consists of clearly identifying the DSPs so as not to confuse them with other microprocessors with similar characteristics or with other semiconductor components that perform the same function analogically (Table 2).

Up until the end of the 1970s, signal processing was achieved, in large part, by using analogic techno-

TABLE 2. Semicondutor devices and components

Digital	Logic	Field-programmable gate arrays Mask-programmable gate arrays Standard-cell ASICs Full-custom ASICs	
		General-purpose circuits	Microprocessors Microcontrollers **Digital signal processors** Others
	Memory	RAMs	Dynamic RAMs Static RAMs Non-volatile RAMs Specialized
		ROMs	Mask-programmable Field-programmable
Analog	Sensors and transducers: sound, light, pressure, others Amplifiers, mixers, filters, RF circuits Opto-electronics: transmitters, receivers Power electronics Conversion circuits: analog-to-digital, digital-to-analog		

logies. The appearance of the first DSPs in approximately 1979 provoked a discontinuity in the technology of signal processing, shifting all analogic systems towards digital systems. The main problems that arise with signal processing systems based on analogic electronics are their low versatility and limited capacity for processing complex algorithms. Versatility depends on the programming possibilities of the device. In spite of the fact that analogic processing systems can incorporate the characteristic of programmability, they are not comparable to what a DSP, designed specifically for signal processing, can offer. In fact, a DSP enables the programming of any algorithm that will determine the desired signal treatment. The DSPs are essentially high speed microprocessors designed to develop signal processing algorithms with elevated calculations.

In a DSP, the limitation at the time of executing an algorithm for signal processing is its velocity. Digital procedures are found to be disadvantageous in applications where great speed is required. Therefore, it is essential to realize them by using analogic techniques. It is important to point out that, due to technological improvements and the optimization of informal structures, the speed of DSPs has been increasing dramatically in recent years. Nonetheless, analogic signal processing is not likely to disappear. Currently a gradual transition in signal processing technologies is taking place. It is necessary to consider that the first DSPs were quite slow and although they solved the problem of complicated assembly, when the demand for greater velocity increased, it was necessary to turn to analogic technology.

3.1.2 Incidence of DSPs in information and communication technologies (ICTs)

In order to complete the selection of the technology of DSPs, it is necessary to evaluate the role that DSPs play in relation to the technological system in which they are immersed. It is quite clear that DSPs and all semiconductor devices are the foundation of microelectronic technologies and the support of the entire technological system of information and communication technologies (ICTs). This system includes all techniques that are related to the generating, transmission, reception, storage and processing of information, as much for human communication as for that among machines. The spectrum of technologies that embraces this definition is extensive as it includes very concrete applications (automatic, robotic, artificial intelligence) that can be used in different environments as well as support technologies (microelectronic, optoelectronic). Therefore, ICTs can be characterized as a technological system whose modules constitute a chain in which each link uses, out of necessity, the previous one until the final applications are realized. This concept is visualized in Fig. 7, in which the different elements that form the technological system of ICTs are defined: support technologies, information and communication technologies in the strictest sense, derived technologies, and complementary technologies.

DSPs are the base of this technological chain and fulfill the task of supporting the functional development of ICTs. The technologies that are incorporated into the DSPs have no utility themselves if they are not applied in their natural area of incidence. There-

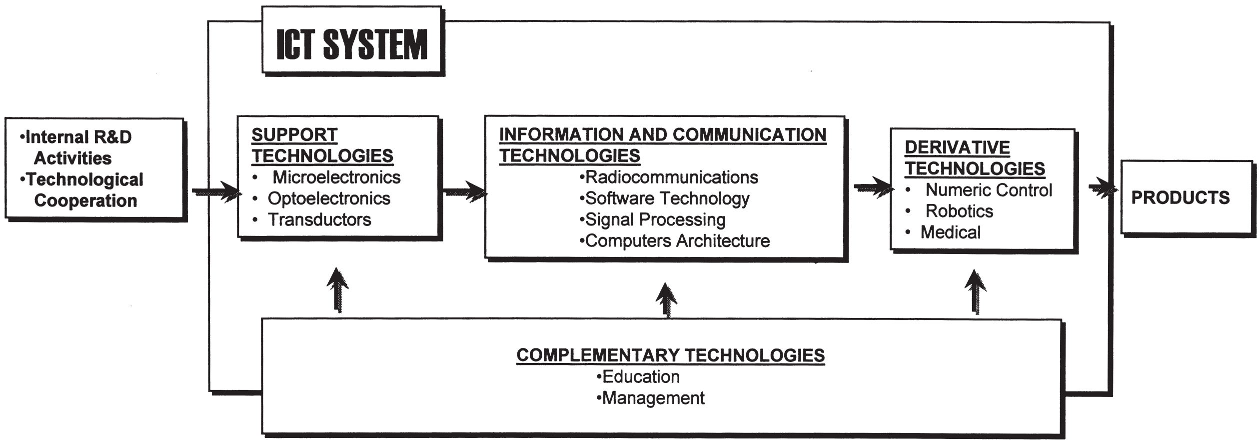

Fig. 7. Information and communication technologies system.

fore, DSPs, being typical support technologies, facilitate the realization of the majority of functions that are required in the equipment and the systems that are used by ICTs.

The large growth of these devices that the market is experiencing and the optimistic expectations regarding their development in the future can be explained by their multiple applications in the scope of ICTs. In addition, DSPs using digital techniques have made processing possible in real time of signals of elevated width band and have provoked a clear breaking-off with the analogic technologies used to date. It has been confirmed that the revolution that these devices have provoked can be compared to the one that the first microcomputers caused in the 1970s.

Digital computing tasks can be divided into two classes. Data processing operates on numbers that represent textual and numerical information. Signal processing operates on numbers that represent real-world signals such as speech and vision. Data processing applications have dominated the computer market and the semiconductor components market over the past decades. DSPs components will become a major growth area in the semiconductor components market over the next few years for two reasons (Price Waterhouse, 1994):

- *Applications pull* such as digital audio for entertainment (Compact Disc, Digital Audio Tape), digital telecommunications (ISDN), digital TV, video-conferencing, speech input and output to computers, and computer vision.
- *Technology push* such as increased processing speeds, greater storage capacities and new algorithms.

3.2 Second phase: definition of an indicator of the technology performance

After having identified the technology of DSPs and evaluated its impact on the system of ICTs, it is necessary to define a parameter that allows for the true evaluation of its performance. This second phase has transcendental importance, as one incorrect definition of the performance parameter could invalidate the analysis results. The definition of this parameter poses some problems which, in research done to date, have been resolved in different ways.

In some studies the technology performance has been estimated based on scientific/technical efficiency indicators, without taking into account commercial aspects. In this way, Roussel (1984) modeled the rate of performance increase of the resilient foam cushioning technology based on the number of related scientific articles that were published. In his study, Roussel's underlying hypothesis is that increments in the number of significant publications about a determined technology reflect increments in the level of understanding of it, which normally is converted into improvements in the products that incorporate it. Nonetheless, this is often not the case. Progress in scientific understanding about a determined technology does not always translate into identifiable improvements for the marketplace.

On the contrary, other studies have measured the technology performance with criteria and variables of a commercial nature. In this way Becker and Speltz (1983, 1986) estimated the performance increments of different chemical compounds for the production of insecticides based on the number of new products that were introduced into the marketplace. These authors maintain that a new chemical compound represented some improvement in terms of cost, spectrum, market niche and the like over those products already in the marketplace. The problem with this indicator is that the degree of newness of a product does not necessarily reflect an increase in technical efficiency. It is true that consumers often associate the modification of certain product qualities with technological improvement. Nonetheless, defining a parameter based exclusively on commercial criteria is of little use when making technological decisions. It must be understood that researchers and engineers in the R&D department can only quantify their findings in the development of a determined technology by using physical/technical units.

Foster (1986a) emphasizes that the parameter must reflect technical characteristics which are easily measurable and, at the same time, recognizable by the clients. On the one hand it should reflect the expressed performance in physical/technical units. It is highly recommended that it be defined by engineers from the firm using variables that are easily quantifiable by the personnel of R&D. At the same time, it should reflect perfectly identifiable attributes or qualities which synthesize the most significant properties and characteristics of the technology in accordance with their impact on the marketplace. In this way, any increment in the physical/technical performance of a technology will also reflect an improvement in the contributions of the products that incorporate it.

Additional difficulties can arise when defining the indicator. The main problem is related to the selection of the most adequate performance parameter for evaluating a specific technology. In this way, Lee and Nakicenovic (1988) have suggested elaborating a wide range of alternative indicators using a process of trial and error to reject the most ineffecient.

Another problem has to do with the engineer's tendency to define performance parameter on the basis of *fundamental* physical variables instead of considering physical variables of *configuration*. This difficulty has been pointed out by Ayres (1994) after analyzing the performances of different technologies (vacuum technology, semiconductors, computers, particle accelerators). According to Ayres, the technology performance should be defined using variables that reflect intrinsic properties of the materials that are employed and in the configurations in which they are used (*configuration variables*). On the contrary, if the parameter is defined on the basis of variables that are used in the enunciation of fundamental physics laws (*fundamental variables*) they would produce biases in estimating performance. In fact, the factors that limit performance increases of a technology are related to the physical properties of the materials that configure it at that moment. It is obvious that the fundamental laws of physics establish a definite limit to the development of any technology, but this is of little interest since the limit is rarely attained.

Finally, cultural differences and communication barriers that exist bewteen the R&D engineers and marketing personnel can cause additional difficulties. This problem has been widely studied in management literature (Brockhoff and Chakrabarti, 1988; Gupta *et al*., 1986; Norton *et al*., 1994). In order to resolve it, numerous solutions have been proposed: developing in-service programs to facilitate communication and understanding among the personnel of both R&D and marketing departments (Millar, 1989); the implantation of organizational structures to favor interdepartmental cooperation (Carroad and Carroad, 1982); regular, short-term transfers of personnel from both departments (Schmitt, 1985; Souder, 1980), etc. All these measures contribute to making both groups increase their field of vision from what they consider their own responsibilities (Szakonyi, 1988). In this way, on the one hand, the technicians would concern themselves more with the needs of the clients, and on the other, those on the commercial end would understand the technical difficulties.

3.2.1 DSPs' efficiency parameter

As with all complex mechanisms, DSPs have numerous characteristics that can be used as technology performance indicators: longitude of data with which it can work, internal memory, capacity to direct memory, etc. In Table 3 we can see the main technical characteristics of a sample of 29 DSPs that were introduced into the marketplace between 1976 and 1995. In the last column the parameter *efficiency* values are indicated. This parameter has been defined on the basis of two characteristics of the technology of DSPs which are easily quantifiable by R&D engineers: cycle time and data time. The *efficiency* parameter can be obtained by dividing the data type with which the DSP can work and its cycle time. The results are standardized with respect to the information received for ADSP21060.

After evaluating different alternative indicators, we have opted to define efficiency based on cycle time and data time for two fundamental reasons: (1) they are the most representative characteristics of the total sum of configuration variables, as they depend on the properties of the semiconductor material that is used (silicon) and on the current architecture of the microprocessors; and (2) they directly affect the pro-

TABLE 3. Main characteristics of a sample of 29 DSPs

Year	Model	Family	Manufacturer	Data type	Cycle time (ns)	Efficiency
1978	S2811	Fixed	AMI	12	300	1.0037E-36
1980	uPD7720	Fixed	NEC	16	250	1.9275E-35
1982	TMS32010	Fixed	Texas Instruments	16	390	1.2356E-35
1982	HD61810	Fixed	Hitachi	12	250	1.2047E-36
1983	MB8764	Fixed	Fujitsu	16	100	4.8188E-35
1983	6386	Fixed	Toshiba	16	250	1.9275E-35
1985	TMS32020	Fixed	Texas Instruments	16	195	2.4765E-35
1985	uPD77220	Fixed	NEC	24	100	1.2353E-32
1985	WEDSP32	Floating	ATT	24E8	160	0.1562
1986	ADSP2100	Fixed	Analog Devices	16	125	3.8551E-35
1986	LM32900	Fixed	National	16	100	4.8188E-35
1986	uPD77230	Floating	NEC	24E8	150	0.166
1987	TMS320C25	Fixed	Texas Instruments	16	100	4.8188E-35
1987	DSP56000	Fixed	Motorola	24	74	1.6671E-32
1987	MB86232	Floating	Fujitsu	24E8	150	0.166
1988	DSP16	Fixed	ATT	16	55	8.7617E-35
1988	ADS2101A	Fixed	Analog Devices	16	80	6.0235E-35
1988	WEDSP32C	Floating	ATT	24E8	80	0.312
1988	TMS320C30	Floating	Texas Instruments	24E8	50	0.5
1990	TMS320C50	Fixed	Texas Instruments	16	50	9.6375E-35
1990	ADSP21010	Floating	Analog Devices	24E8	50	0.5
1992	ADSP21020	Floating	Analog Devices	24E8	30	0.833
1992	DSP32C	Floating	ATT	24E8	50	0.5
1993	TMS32C50	Fixed	Texas Instruments	16	40	1.2047E-34
1993	TMS320C30	Floating	Texas Instruments	24E8	40	0.625
1994	DSP1610	Fixed	ATT	16	25	1.9275E-34
1994	TMS320C31	Floating	Texas Instruments	24E8	33	0.758
1994	ADSP21060	Floating	Analog Devices	24E8	25	1
1995	TMS320C5x	Fixed	Texas Instruments	16	25	1.9275E-34

duct offerings that incorporate DSP components and they are easily identifiable by their users.

Nevertheless, these characteristics will have greater importance according to the application that the user wishes to carry out. It can be believed that the most important of these qualities is the processing speed (*cycle time*). In Fig. 8, the evolution of cycle time can be observed. The time consumed in processing an instruction has gone from 300 split seconds in 1979 to 25 in 1995. In the first approximation, this progressive reduction in the instruction cycle duration reflects an increase in the DSPs' technology performance.

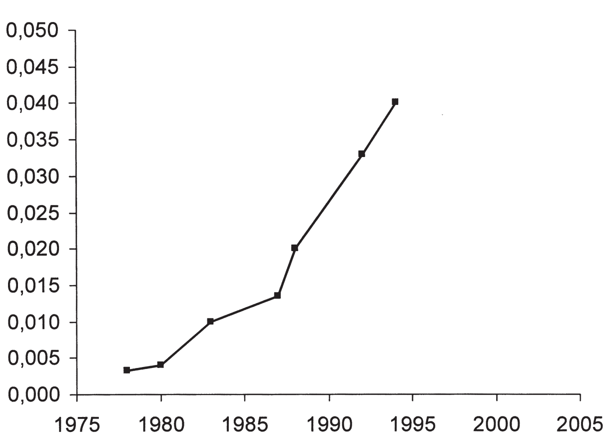

Fig. 8. Cycle time evolution.

However, the parameter cycle time in itself cannot sufficiently explain the performance of the DSPs. It is possible to find one device with less speed than another which is, at the same time, capable of realizing operating calculations with a higher performance. Therefore, it is necessary to consider another factor, equally as important as the speed of processing: the format that is used to represent the data (*data type*). If this parameter is considered, processors can be broken down into two families: those that operate in *fixed point* and those that do so in *floating point* (see Table 3). With the first format an inferior values ranking of data type is obtained. On the other hand, the floating point is a more dynamic margin and a greater volume of data can be treated. To evaluate the performance obtained from the technologies of the DSPs, the two families should be analyzed.

3.3 Third phase: construction of the S curve

Once a technology performance indicator is defined, it is necessary to construct the S curve. Constructing the S curve consists of representing the technology performance evolution based on an explicatory variable. To do this, Foster (1986a) recommends relating the performance improvements with the effort expended in the development of the technology. Without any doubt, the technology effort variable has great explicatory capacity. To measure this variable, numerous indicators have been proposed: expense volume in R** Unknown entity - D ** the number of researchers and engineers dedicated to R** Unknown entity - D ** years of research, etc. Nonetheless, the problem that occurs when it comes to obtaining concrete data about the effort expended by a specific firm in the development of a concrete technology is noteworthy. The strategic nature of this information makes the firms resist spreading this data, which, in turn, makes the creation of empirical studies quite difficult.

Most of the published studies have resolved this problem by using the dimension of time to construct the S curve. In this way, the research of Roussel (1984), Becker and Speltz (1983, 1986), Lee and Nakicenovic (1988), Hilbrink (1990) and Ayres (1994) regarding the impossibility of obtaining information about the technology effort has represented the evolution of the performance parameter based on time.

Along the same lines, the analysis of DSP technology was realized as a result of the temporal evolution of the efficiency parameter. We are aware that this option does not fulfill one of the basic recommendations made by Richard Foster. To a certain extent, by relating the evolution of technology performance with time, instead of expressing it based on the technological effort, one of the fundamental elements of the S curve model is being modified. We concur with Foster in pointing out that the mere passage of time does not provoke performance increments in a technology and that the time variable, in itself, lacks explicatory capacity.

Nevertheless, solid arguments can be found to justify the representation of the S curve based on time. In the first place, the definition of the S curve could be justified based on time using the same arguments that support the use of time series models in other fields. Time series models have been and are used in varying fields of economy and management with impressive success. These models allow for the behavior analysis of variables and establish predictions about future values bases on historical data.

Representing technology performance based on time is an attempt to explain its evolution by using the analysis of its behavior in the past. This claims: (1) to accept that the technology performance variable has the capacity to explain itself; or (2) on the contrary, to recognize the impossibility of relating its behavior with other variables. According to this last alternative, the temporal dimension of the S curve model would hide a multitude of potentially explicatory variables that the researcher cannot quantify.

Developing this argument, Butler (1988) pointed out that the accumulation of knowledge is the principal explicatory variable behind performance increases of a technology. Influencial scholars (Utterback, 1994; Nelson and Winter, 1982) have attributed a significant role to the experiential effect and to the accumulation of knowledge in the process of innovation technology. Recently, Nonaka and Takeuchi (1995) have studied the learning processes, identifying the factors that determine the accumulation of knowledge. According to this research, claiming to explain the improvement in the performance of a specific technology exclusively by using the increases in expenses in R&D and/or in the number of researchers is an oversimplification of reality.

It has been pointed out that there are numerous factors that are difficult to quantify which are related to (intangible) resources and (dynamic) capabilities that directly affect the results of effort on R&D in a concrete firm (Mahoney and Pandian, 1992; Peteraf, 1993). Only if the technological effort makes learning and accumulation of knowledge easier will the results indicate an increase in technology performance. This implies that the performance increment of technologies is not a lineal process. This is a long, uncertain and accumulative process in which the past conditions the future and where there is a lack of economies with respect to time (Dierick and Cool, 1989). The technological effort that contributes to the accumulation of knowledge about a technology, as with other intangible claims of a firm, constitutes, at the same time, an input and an output (Imai, 1987). In addition, technological understanding is quite tacit and therefore difficult to quantify.

These observations add arguments that contribute to the justification of the construction of the S curve based on a temporal dimension. Recognizing the influence of the learning process implies reducing the explicatory capacity of the technological effort variable. The results of the effort expended in the development of a technology will depend, to a large extent, on the learning capacity of the firm that gives the very magnitude of effort. Consideration of the learning effect and the difficulty in estimating the value of the technological effort, have made the performance evolution of DSPs based on time advisable.

3.3.1 Evolution of the technological performance of DSPs

In accordance with previous reflections of the anaylsis of the technology performance of DSPs, the evolution of efficiency parameter values over time should be represented. Fig. 9 shows us the perform-

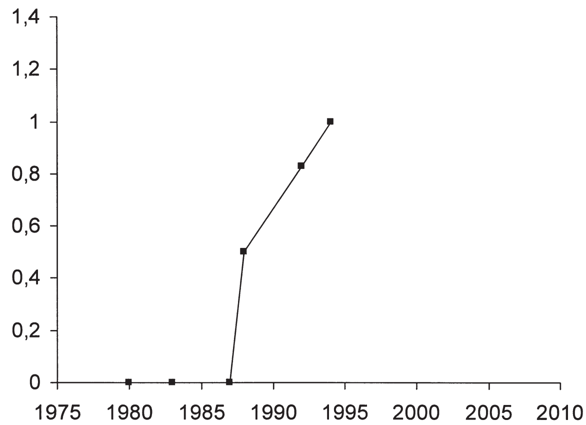

Fig. 9. Efficiency evolution.

ance evolution of DSPs in general, including those of fixed point as well as those of floating point. The efficiency values have been represented only for those years in which an improvement is produced. It is possible to observe that the efficiency of the family of DSPs that work in fixed point is practically non-existent, while the evolution of the efficiency of the DSPs that work in floating point increases exponentially starting in 1985. This is because, in the first family the evolution of data type was negligible and the instruction cycle time diminished slowly, while in the second family the data type takes off, as the instruction cycle time diminishes. In this way, efficiency increases considerably. In this figure two phases can be distinguished. One phase stands out during the first few years (1978–1985) in which performance scarcely increases. After that period, which could be characterized as an apprenticeship, and as a result of accumulated knowledge, the technology improves its performance in a way that becomes exponential from 1987 on.

The next issue that is discussed in this analysis is that of estimating the efficiency limit of the family of DSPs that work in floating point. Of all the applications used to determine performance limits, the S curve model is possibly the most well-known. Knowing when a technology has reached its perfomance limit is vitally important to a firm. This information should help to orient its technological strategy, as the proximity to limits increases the probability that technological ruptures may be produced. In this situation, investing resources in the development of a technology that is near its limits accentuates the risk of not obtaining the anticipated technological performances. The appropriate thing to do would be to invest in the development of technologies of an emerging nature.

The main difficulty that arises when it comes to determining the performance limit of a technology is estimating, beforehand, the precise data to represent the final phase of the S curve. From a mathematical point of view, in order to represent a logistical function, it is necessary to know (Foster, 1986a): a certain number of historical values, the inflection point and the superior limit or an estimation of time that it takes to reach it. To resolve this problem, Foster suggests approximating these values with qualitative provision techniques. However, it should be emphasized that the principal usefulness of the S curve model is in analyzing the evolution of performances in order to understand what has happened and to verify the rationality of the technological strategies. Therefore, it seems unreasonable to insist on graphic representations of the S curve of a high degree of precision.

Fig. 10 shows the forecasted evolution of the efficiency of floating point DSPs. The estimation was formulated on data obtained to date. It is presumed that in 1994 an inflection point in the logistical function is produced and that the maximum efficiency that can be obtained with this technology is 2. We can see that this family of DSPs is found in an exponential growth phase. This leads us to believe that the ceiling in the efficiency of floating point DSPs will not be reached at least within the next 10 years.

4. CONCLUSIONS

In accordance with the proposed objectives, the conclusions that are drawn in this paper can be grouped into two different categories. Some are observations of a theoretical nature and others are practical recommendations.

The theoretical reflections, that can be found in Section 2, have allowed us to relate the S curve model to diffusion and life cycle models. Initially we attempted to use these relationships to increase the

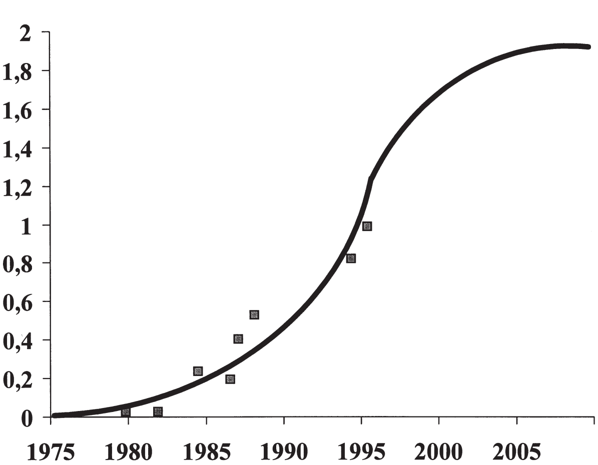

Fig. 10. S curve model and the efficiency evolution of DSPs.

theoretical and analytical consistency of the S curve. For this reason, the origin and conceptual foundations of these diffusion and life cycle models have been analyzed, pointing out the existent similarities between these and the S curve model. With the exception of certain methodological differences, it has become evident that the technological factor constitutes a solid nexus among these models. According to this, the following observations can be made:

- the diffusion speed of a technology depends, to large extent, on the evolution of its technological performance;
- the life cycles of products/industries are conditioned by the evolution of the technology performances that characterize them; and
- of all the life cycle models of technology, the S curve model is the one that best reflects the evolution of technology performance.

With this theoretical analysis, we have intended to contribute to the elimination of the barriers that have traditionally separated research in the fields of economy and management. Progress in both the understanding of technological change and the development of technology management make it essential for us to make an effort to coordinate these two fields of research. The passage of knowledge and the terminological normalization are essential requirements in order to produce significant advances in both the understanding and the nature of the process of innovation technology. With these theoretical conclusions, we have intended to enhance the hypothesis about the existence of conceptual relationships between models of different origins: diffusion models (industrial economy, marketing), life cycle models (strategic management, production management, marketing), S curve and technology life cycle models (technology management). It would be profitable if, in future research, the study of the relationship between these three family models were further investigated. Pointing out empirical contrasts and the analysis of the correlation between the life cycles of products/sectors, diffusion speed and the evolution of the technology performance of different technologies can contribute to this advancement.

The second series of conclusions have a clear practical orientation. The analysis of the technology of DSPs has served to develop an operative methodology that helps to implement the S curve model. The problems that the practical application of the S curve model presents are grouped into three phases that define this methodology: (1) the selection of the technology to be analyzed; (2) the definition of the technology performance indicator; and (3) the construction of the S curve. The analysis of the technology of DSPs using the proposed methodology has allowed us to verify that this technology is found in a stage of growing productivity which is characterized by:

- experiencing exponential increases in performances measured by the efficiency parameter; and
- being even further from having reached the limit of its technological performance.

The relationships that have been defined in the theoretical findings allow us to widen the scope of the conclusions. Based on these relationships, implications of increases in technology performance of DSPs can be derived. In fact, keeping in mind the existing relationship between the diffusion processes of innovations, life cycle models and the S curve model, the following conclusions can be made:

- it is logical to expect the technology of DSPs to be adopted by a growing number of enterprises, and to experience large diffusion in the coming years;
- considering DSPs as intermediate products that are incorporated into other final products (since they are support technologies in the system of ICTs) their sales will increase extraordinarily; and
- these technologies will modify the life cycle of the products that incorporate them, generally by prolonging it. The same could be said of the evolution of industrial sectors where these technologies are applied.

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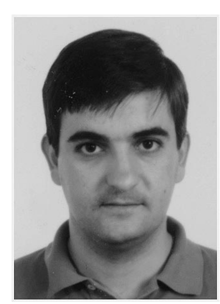

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