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Stochastic Performance Modelling and Management for Technological Systems

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XX Ciclo di Dottorato

Introduction

In the last decades, the continuous acceleration of the technological changes has shown the importance of the technology and innovation management for competitive advantage and survival. Therefore, the technological innovation process is until now a topic of huge research. Indeed the words *technology* and *innovation* are objects of discussion. However, for the purposes of this study, we define technology as a process, technique, or methodology – embodied in a product design or in a manufacturing or service process – which transforms inputs of labour, capital, information, material, and energy into outputs of greater value. Then, we define technological innovation as a change in one or more of such inputs, processes, techniques, or methodologies, which improves the measured levels of performance of a product or process (Christensen, 1992a).

In the technology management literature, growth curves (also called *S-curves*) have been extensively used to model the performance and to analyze the life cycle of many technologies in spite of their limits. In fact, if on one side they are effective in describing the global trends in the industrial sectors (at the industry-level), on the other side they have more limited decision-making usefulness within the single company (at the company-level) (Christensen, 1992a; Christensen, 1992b). Moreover, the deep statistical understanding of the dynamics of technological innovation process is a fundamental phase in its management. To this end, the formulation of the diagnostic tools aimed to analyze different representative scenarios is mandatory. In fact, while the innovation is one of the main drivers of a company's competitive advantage, it has often a disruptive effect on the organization because it is associated to or induces organizational change and adaptation (Calia *et al.*, 2007; Fosfuri & Ronde, 2006). Therefore, a technological change is a full-scale change in the way business is conducted and the simple adoption of new technology may be insufficient in order to survive (Grove, 1999). In particular, companies must implement a dual management mode because management approaches used in periods of stability are often quite inappropriate in periods of significant changes (Dervitsiotis, 2003; Dervitsiotis, 2004). Consequently, only through a timely organizational change, companies can strategically transform themselves before the decline phase starts.

This thesis consists of four chapters. The common subjects are the performance modelling and the technology and innovation management. It is organized in the following manner. In the Chapter 1, some S-curve models are discussed with respect to their genesis and their statistical-mathematical properties. In the Chapter 2, the concept of "force of change" is proposed. It measures the incentive to substitute the adopted technology. Moreover, a new flexible S-curve model is formulated and its statistical-mathematical properties are evaluated. In the Chapter 3, the S-curve as a benchmarking tool is proposed in order to overcome the difficulty to practically use S-curve as a decision-making tool at the company-level. Moreover, two operative functions are reformulated in order to discriminate amongst typical behaviours of a company against accumulated "performance delays" and "performance distances" with respect to the leader in the specific industrial sector. Finally, in the Chapter 4, a piecewise regression model is proposed in order to identify if a critical environmental change has occurred and a strategic transformation is needed for survival. In particular, the diagnostic power of this model is highlighted through the analysis of the aircraft industry history.

Chapter 1 A Comparison amongst the S-curve Models for Technological Performance Growth

1.1. Introduction

The S-curve models were firstly formulated to study population growth and diffusion phenomena over time (Carrillo & González, 2002; Kumar & Kumar, 1992; Linton, 2002; Meade & Islam, 1995; Meyer *et al.*, 1999; Teng *et al.*, 2002). Subsequently, they were proposed by Richard Foster (1986) in order to analyze the evolution of the technological performance (Asthana, 1995; Erto, 1997a; Erto & Lanzotti, 1995; McGrath, 1998; Nieto *et al.*, 1998). The S-curve is able to describe how a technological performance parameter, $P(t)$, increases as a function of the Research & Development (R&D) effort or, if R&D is constant, of time, t, until it approaches its saturation value. In particular, at the beginning growth is slow owing to initial difficulties. Once a critical mass of engineering expertise in the technology builds up, growth is rapid and its progress is accelerated. However, as the saturation value is approached, growth decelerates until it finally stops (Figure 1.1).

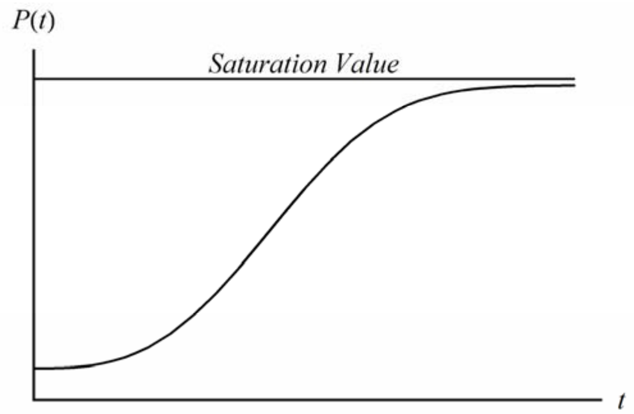


Figure 1.1. The S-curve model

Foster (1986) pointed out that the growth of a new technology must never be represented in terms of time, but rather in terms of the R&D effort (measured in monetary units, number of researchers, hours worked, workers per year, etc.). Nonetheless, the difficulties associated with obtaining data about the investment that is made by different companies (companies are reluctant to spread this strategic information) in the development of a specific technology are often insuperable. Consequently, the mathematical functions proposed in the literature model the technological performance according to the time (Nieto *et al.*, 1998). In fact, even if this assumption doesn't fulfil one of the basic recommendations in the use of S-curves, it allows to describe the significant role of the experiential effect and accumulation of knowledge in the technological growth process.

However, the proliferation of various models and the differences and similarities amongst them make difficult for a model user the choice of the appropriate model for his data and situation (Kumar & Kumar, 1992). The models differ amongst themselves in terms of their genesis and their quantitative characteristics. In this work, a comparative study of the characteristics of some S-curve models is proposed. In particular, the four different facets of the comparative evaluation are as follows:

1. the genesis;
2. the number of parameters;
3. the location of their inflection point and the symmetric or nonsymmetric behaviour about it;
4. the closeness to linear behaviour.

The last feature is studied by fitting the S-curve models to real datasets concerning three different technologies: jet aircraft engines, piston aircraft engines and digital signal processors (DSP).

1.2. Genesis and mathematical properties of some s-curve models

In general, growth models are mechanistic rather than empirical ones. A mechanistic model usually arises as a result of making assumptions about the type of growth, writing down the differential equation that represent these assumptions and, then, solving this equation to obtain a growth model (Draper & Smith, 1981). Several mathematical functions have been proposed in the literature as S-curve models. Among them, the logistic model and some of its generalizations (the log-logistic model and the Richards model), the Gompertz model, the Erto-Lanzotti model and the Weibull-type model are compared in this work. The Table 1.1 summarizes the mathematical properties for the examined S-curve models.

Table 1.1 The mathematical properties of the compared S-curve models

Model	**Formula**	**Parameters**	P_0	**Coordinates of the inflection point** $(t^*, P(t^*))$
Logistic	$P(t) = \frac{P_{\lim}}{1+e^{\alpha-kt}}$	$\alpha > 0$ $k > 0$	$\frac{P_{\lim}}{1+e^{\alpha}}$	$t^* = \frac{\alpha}{k}$, $P(t^*) = \frac{P_{\lim}}{2}$
Gompertz	$P(t) = P_{\lim} e^{-e^{\alpha-kt}}$	$\alpha > 0$ $k > 0$	$\frac{P_{\lim}}{e^{e^{\alpha}}}$	$t^* = \frac{\alpha}{k}$, $P(t^*) = \frac{P_{\lim}}{e}$
Log-logistic	$P(t) = \frac{P_{\lim}}{1+e^{\alpha-k\ln(t)}}$	$\alpha \in R$ $k > 1$	$\lim_{t\to 0} P(t) = 0$	$t^* = \left(\frac{e^{\alpha}(k-1)}{k+1}\right)^{\frac{1}{k}}$, $P(t^*) = P_{\lim}\frac{k-1}{2k}$
Erto-Lanzotti	$P(t) = P_0 + (1-e^{-kt^s})(P_{\lim} - P_0)$	$k > 0$ $s > 1$	P_0	$t^* = \left(\frac{s-1}{ks}\right)^{\frac{1}{s}}$, $P(t^*) = P_0 + (1-e^{\frac{1-s}{s}})(P_{\lim} - P_0)$
Richards	$P(t) = \frac{P_{\lim}}{(1+e^{\alpha-kt})^{\frac{1}{s}}}$	$\alpha > \ln s$ $k > 0$ $s > 0$	$\frac{P_{\lim}}{(1+e^{\alpha})^{\frac{1}{s}}}$	$t^* = \frac{\alpha - \ln s}{k}$, $P(t^*) = \frac{P_{\lim}}{(1+s)^{\frac{1}{s}}}$
Weibull-type	$P(t) = P_{\lim} - \alpha e^{-kt^s}$	$0 < \alpha < P_{\lim}$ $k > 0$ $s > 1$	$P_{\lim} - \alpha$	$t^* = \left(\frac{s-1}{ks}\right)^{\frac{1}{s}}$, $P(t^*) = P_{\lim} - \frac{\alpha}{e^{\frac{s-1}{s}}}$

The used notation is:

t is the explanatory variable representing the time;

$P(t)$ is the response variable representing the technological performance level;

P_0 is the original value of the technological performance level (corresponding to $t = 0$);

$P_{\lim}$ is the saturation value (or limit) of the technological performance level;

$(t^*, P(t^*))$ are the coordinates of the inflection point;

α, k and s are the model parameters.

We considered P_0 and $P_{\lim}$ as given constants, while α, k and s are to be estimated. In fact, the overparameterization problem often occurs when the user tries to estimate the saturation value like a parameter of the model (Erto, 1997a; Erto & Lanzotti, 1995; Ratwosky, 1990).

1.2.1 The logistic model

Introduced by Verhulst (1838), the logistic model was popularized in mathematical biology by Lotka (1920). Its genesis is related to population growth processes (Meyer *et al*., 1999). The model was formulated as solution of a differential equation and assumes that at the beginning the growth rate of a population is proportional to the population itself (exponential growth). Then, because few, if any, systems are permanently unbounded and sustain exponential growth, the introduction of a saturation limit gives rise to the more realistic sigmoidal shape. The logistic model is a two-parameter model and it is symmetric with respect to its inflection point. In fact, the inflection point occurs in correspondence of the 50% of the saturation value of the technological performance level ($P_{\lim}/2$).

1.2.2 The Gompertz model

Closely related to the logistic model is the Gompertz model (Gompertz, 1825). Its genesis was formulated as solution of a differential equation as well as the logistic model one. It assumes that the growth rate of a population is a function of the logarithm of the saturation limit (Teng *et al*., 2002). The Gompertz model is a two-parameter model and it is not symmetric with respect to its inflection point. In fact, the inflection point occurs in correspondence of the 37% of the saturation value of the technological performance level ($P_{\lim}/e$, where e represents the base of the natural logarithm).

1.2.3 The log-logistic model

Introduced by Tanner (1978), the log-logistic model directly derives from the logistic model through the replacement of the time t by $\ln(t)$ (Meade & Islam, 1995). It is a two-parameter model and it is not symmetric with respect to its inflection point. In fact, the inflection point occurs before the technological performance level reaches half of its saturation value ($P(t^*) < P_{\lim}/2$).

1.2.4 The Erto-Lanzotti model

Introduced by Erto & Lanzotti (1995), it has a peculiar genesis that is directly linked to the technological innovation process. In fact, this model arises from the analysis of the interactions between the two main factors that play a leading role in starting the innovation process: the inertia toward change process and the stimulus toward the improvement process. The Erto-Lanzotti model is a two-parameter model and it can offer wide variations in the degree of symmetry for a given inflection point. In fact, the inflection point can assume a wide range of values. This property is a peculiarity of the so-called *flexible* models.

1.2.5 The Richards model

The Richards model represents the most popular flexible S-curve since it was the first proposed flexible model (Richards, 1959). On the other hand, this flexibility was obtained at the cost of a greater computational complexity. In fact, this model was formulated by adding a third parameter, s, to the original formulation of the logistic model (Birch, 1999). When $s = 1$ the Richards model matches the logistic model, but for $s > 1$ the inflection point occurs when $P(t) > P_{\lim}/2$ and for $s < 1$ it occurs when $P(t) < P_{\lim}/2$. This allows a wider range of curves to be produced, but as $s \to 0$ the lowest value of $P(t^*)$ remains greater than $P_{\lim}/e$. In fact, as $s \to 0$ the Richards model tends towards the Gompertz one. Therefore, the Richards model is a three-parameter model and it can offer wide variations in the degree of symmetry for a given inflection point.

1.2.6 The Weibull-type model

Unlike the other growth models, the Weibull-type model derives from a morphological analogy rather than theoretical remarks (Prodan, 1968). In fact, the idea of applying this probability function to the growth analysis was suggested by the analogy between a growth curve and a cumulative distribution function and by flexibility of the Weibull distribution function. Then, the S-curve was obtained by adding an expanding factor ($P_{\lim}$) to the Weibull distribution function since it is scaled to yield a probability domain between 0 and 1 (Yang *et al.*, 1978). The modified Weibull function is highly flexible. Therefore, the Weibull-type model is a three-parameter model and it can offer wide variations in the degree of symmetry for a given inflection point.

1.2.7 Discussion

As anticipated, the above growth models differ mainly on the basis of three important characteristics:

1. the genesis;
2. the number of parameters;
3. the location of their inflection point and the symmetric or nonsymmetric behaviour about it.

The genesis is important in order to understand the underlying dynamics of the models. The Erto-Lanzotti model is the only one that derives from the identification of the main forces that rule the innovation process, being all the other models originated in different contexts and, then, adopted to model the technological performance growth.

The number of parameters determines the computational complexity. In fact, the application of any model involves estimating its parameters. The greater the number of parameters, the better the data will fit. On the other hand, the job of estimating becomes complex (Kumar & Kumar, 1992). Amongst the compared models, the Richards and the Weibull-type models have one more parameter than the other models.

The point $(t^*, P(t^*))$ at which the growth rate of the technological performance is at its peak is indubitably an important characteristic of the process. In real world situations, this point can be anywhere in the process of development. Therefore, the S-curve can be symmetric as well as nonsymmetric (Kumar & Kumar, 1992). One of the weaknesses of earlier models was that they were either symmetric or nonsymmetric. In fact, the logistic and the Gompertz models have their inflection points at 50% and 37% of the saturation value of the technological performance level, respectively. Thus, they are symmetric and nonsymmetric about the inflection point, respectively. The log-logistic model has its inflection point within a range between 0% and 50% of the saturation value of the technological performance level. Thus, it is nonsymmetric about it. Instead, the flexible models, such as the Erto-Lanzotti, the Richards and the Weibull-type models, overcome this limit since they can offer wide variations in the degree of symmetry for a given inflection point.

Finally, the Erto-Lanzotti model is the only one that assumes an original value of the technological performance level (P_0) explicitly. On the contrary, the log-logistic model assumes $\lim_{t \to 0} P(t) = 0$ and the other models assume P_0 depending on the model parameters.

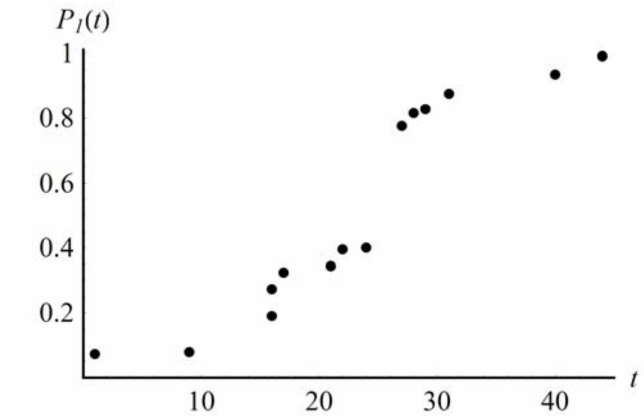
1.3. The closeness to linear behaviour

The S-curve models are nonlinear regression models since their parameters appear nonlinearly. In this work, the basis for estimating the unknown parameters in all the models is the criterion of least squares (LS). So, an amount ε, which is an unobservable random "error" term, was added to the models. If the error terms are independent and identically distributed normal random variables with mean zero and finite variance σ^2, the LS estimators in linear models are also the maximum likelihood estimators of the parameters. They are minimum-variance unbiased linear estimators. Therefore, they provide the best available estimates in practice. Moreover, they are normally distributed. On the contrary, in nonlinear models the LS estimators have essentially unknown properties for finite sample sizes (only asymptotically nonlinear LS estimators have the properties possessed by linear ones). These and other desirable properties, as we will illustrate in subsequent paragraphs, make important assessing nonlinearity in nonlinear models. In fact, it is self-evident that a *close to linear* nonlinear model is to be preferred to one whose behaviour is *far from linear* (Bates & Watts, 1980; Bates & Watts, 1998; Draper & Smith, 1981; Ratkowsky, 1983). Therefore, the nonlinear behaviour of the above S-curve models was evaluated by fitting them to real datasets concerning three different technologies. Obviously, it is more appropriate to speak of a "model/dataset" combination, rather than of a “model”, since a specific set of observed data in conjunction with a specified model determines its behaviour.

In the Tables 1.2, 1.3 and 1.4 and in the Figures 1.2, 1.3 and 1.4 some data concerning the growth towards the saturation value of the performance level (at the industry-level) of the following technologies are presented: jet aircraft engines, piston aircraft engines and digital signal processors (DSP). The take-off thrust, $Y_1(t)$, (in Newton, N) of jet aircraft engines; the engine power, $Y_2(t)$, (in kilowatt, kW) of piston aircraft engines and the efficiency (defined as the ratio between the data type that the DSP can work and its cycle time), $Y_3(t)$, (in bit/nanosecond, bit/ns) of DSP, have been adopted as performance indicators (Erto, 1997a; Nieto *et al.*, 1998). From the adopted t scale, the simple proportion $\frac{P_1 - P_0}{t_1 - t_0} = \frac{P_2 - P_1}{t_2 - t_1}$ (where P_k is the performance level corresponding to time t_k with $k = 0,\ldots,n$ and n is the sample size) leads to the following original values (corresponding to $t_0 = 0$) of the technological performance level: 0.071; 0.007 and 0.0732, respectively. Having used the normalized data, the saturation value of the performance level $P_{\lim} = 1$ follows for each dataset.

Tables 1.2 Performance (take-off thrust) data of jet aircraft engines (the saturation value of the take-off thrust level is $Y_{1_{\lim}} = 1.29 \cdot 10^8 N$)

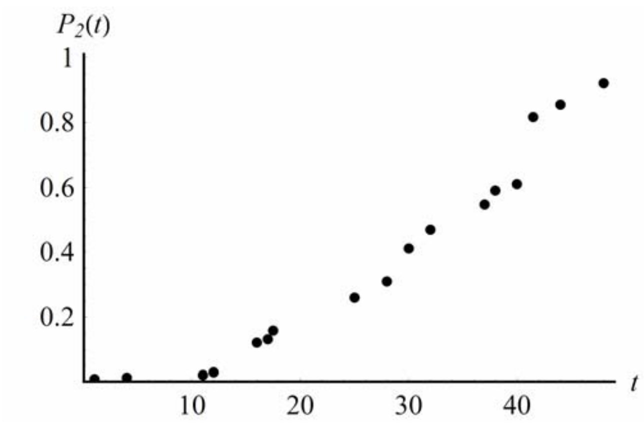
t ($year$)	$Y_1(t)$ (N)	$P_1(t) = Y_1(t) / Y_{1_{\lim}}$
1 (1942)	$9.287 \cdot 10^6$	0.072
9 (1950)	$1.006 \cdot 10^7$	0.078
16 (1957)	$2.451 \cdot 10^7$	0.19
16 (1957)	$3.521 \cdot 10^7$	0.273
17 (1958)	$4.179 \cdot 10^7$	0.324
21 (1962)	$4.437 \cdot 10^7$	0.344
22 (1963)	$5.095 \cdot 10^7$	0.395
24 (1965)	$5.16 \cdot 10^7$	0.4
27 (1968)	$9.997 \cdot 10^7$	0.775
28 (1969)	$1.051 \cdot 10^8$	0.815
29 (1970)	$1.067 \cdot 10^8$	0.827
31 (1972)	$1.129 \cdot 10^8$	0.875
40 (1981)	$1.205 \cdot 10^8$	0.934
44 (1985)	$1.277 \cdot 10^8$	0.99



Figures 1.2. Jet aircraft engine (normalized) data

Tables 1.3 Performance (engine power) data of piston aircraft engines (the saturation value of the engine power level is $Y_{2\lim} = 2835\,kW$)

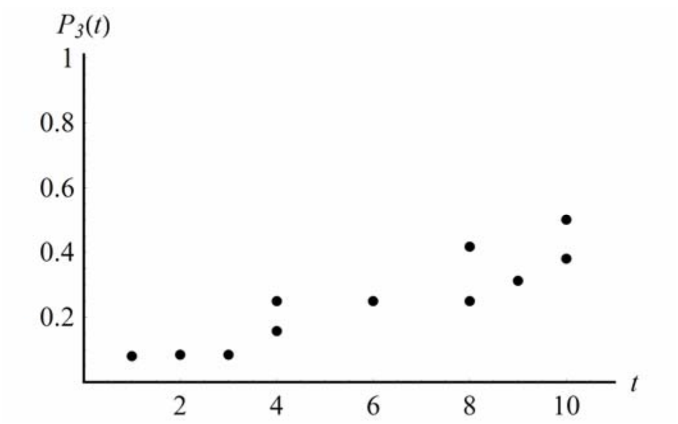
t ($year$)	$Y_2(t)$ (kW)	$P_2(t) = Y_2(t)/Y_{2\lim}$
1 (1902)	22.68	0.008
4 (1905)	34.02	0.012
11 (1912)	56.7	0.02
12 (1913)	79.37	0.028
16 (1917)	340.2	0.12
17 (1918)	368.5	0.13
17.5 (1918.5)	445.1	0.157
25 (1926)	737	0.26
28 (1929)	878.8	0.31
30 (1931)	1162	0.41
32 (1933)	1327	0.468
37 (1938)	1551	0.547
38 (1939)	1672	0.59
40 (1941)	1729	0.61
41.5 (1942.5)	2313	0.816
44 (1945)	2424	0.855
48 (1949)	2611	0.921



Figures 1.3. Piston aircraft engine (normalized) data

Tables 1.4 Performance (efficiency) data of DSP (the saturation value of the efficiency level is $Y_{3_{\lim}} = 2\, bit/ns$)

t ($year$)	$Y_3(t)$ (bit/ns)	$P_3(t) = Y_3(t)/Y_{3_{\lim}}$
1 (1985)	0.1562	0.0781
2 (1986)	0.166	0.083
3 (1987)	0.166	0.083
4 (1988)	0.312	0.156
4 (1988)	0.5	0.25
6 (1990)	0.5	0.25
8 (1992)	0.833	0.4165
8 (1992)	0.5	0.25
9 (1993)	0.625	0.3125
10 (1994)	0.758	0.379
10 (1994)	1	0.5



Figures 1.4. DSP (normalized) data

From Figures 1.2, 1.3 and 1.4 we can see that the jet aircraft engine and the piston aircraft engine datasets are representative datasets since they cover the full range of the response variable $P(t)$ by approaching the saturation value of the technological performance level. On the other hand, the DSP dataset is a critical dataset since it covers just the half of this range. In fact, the estimate efficiency depends on sample size generally. Instead, for the S-curve models the coverage of all the growth phases has a primary effect.

1.3.1 The curvature measures of nonlinearity of Bates and Watts

Most algorithms for computing the least squares estimates and most inference methods for nonlinear models are based on a local linear approximation to the model by a Taylor series expansion (Bates & Watts, 1980; Bates & Watts, 1998). The effect of this approximation is to replace the *solution locus* (that is the expectation surface traced in the $n-$ dimensional sample space) by its tangent plane (*planar assumption*) and simultaneously to impose a uniform co-ordinate system of the parameters on that tangent plane (*uniform co-ordinate assumption*). On the contrary, for nonlinear models the solution locus is a curved surface and the *parameter lines* (the lines on the solution locus corresponding to values of parameters having equal increments) are not straight, parallel and equispaced (Bates & Watts, 1980; Bates & Watts, 1998; Draper & Smith, 1981; Ratkowsky, 1983). Therefore, both the effectiveness of LS algorithms and the validity of inferences made regarding the parameters of a nonlinear model will be affected by the closeness of the model to the linear approximation. In particular, for close to linear models, there will almost always be a unique minimum of the residual sum of squares surface and the speed of convergence of the algorithms to that minimum will usually be very rapid. On the contrary, as the behaviour of a model becomes more and more nonlinear, convergence may not even occur.

The curvature measures proposed by Bates & Watts (1980) provide the modeller with an effective approach in order to evaluate the adequacy of a linear approximation and its effects on inferences. In fact, these authors quantified the extent of curvature of the solution locus and of the parameter lines and their lack of parallelism and equispacedness by two measures: the *intrinsic nonlinearity* (*IN*) and the *parameter effects nonlinearity* (*PE*), respectively. In particular, the *PE* may often be reduced, sometimes drastically, by a suitable model reparameterization. On the contrary, the *IN* cannot be altered by reparameterization. The importance of *IN* becomes manifest when the user wishes to predict values of the response variable and to determine confidence limits for those predicted values. In fact, the estimate bias is related only to the intrinsic component of nonlinearity. Finally, if the *IN* is acceptably low and the modeller finds a reparameterization which has an acceptable *PE*, the following benefits stand: the LS estimates will be easily obtained; the various statistical tests or procedures whose use is derived from analogy with linear models and which assume normality will be valid; the estimate bias will be negligible (Bates & Watts, 1980; Bates & Watts, 1998; Ratkowsky, 1983).

The curvature measures *IN* and *PE* were calculated for each model/dataset combination. They are not very meaningful as they stand. In fact, a convenient scale of reference was established by comparing the curvature measures with that of the linear parameter confidence region at a specified significance level, $1-\alpha$. This curvature is equal to $1/\sqrt{F(p,n-p;1-\alpha)}$, where F indicates the Fisher Distribution, p is the parameter number and n is the sample size (Bates & Watts, 1980; Bates & Watts, 1998; Ratkowsky, 1983). We chose as critical value $1/(2\sqrt{F})$ at 95% significance level, so that the radius of curvature of the solution locus is at least twice the radius of the linear 95% confidence region. In this way, the deviation of the solution locus from the tangent plane – calculated as $100\{1-\sqrt{1-F(IN)^2}\}\%$ – is less than 14% (Bates & Watts, 1980). The results are reported in Table 1.5 with the critical values in brackets. The bold values point out the curvature measures that exceed the critical values.

Table 1.5 The curvature measures of Bates and Watts and the critical values for each model/dataset combination

Data	**Curvature measures**	**Logistic**	**Gompertz**	**Log-logistic**	**Erto-Lanzotti**	**Richards**	**Weibull-type**
Jet aircraft engines	IN	0.1338 (0.2537)	0.2057 (0.2537)	0.1439 (0.2537)	0.1361 (0.2537)	**1.105** (0.2640)	**0.3089** (0.2640)
	PE	0.1685 (0.2537)	0.1817 (0.2537)	0.2079 (0.2537)	**44.90** (0.2537)	**4.174** (0.2640)	**145.3** (0.2640)
Piston aircraft engines	IN	0.09472 (0.2606)	0.1736 (0.2606)	0.1664 (0.2606)	0.09850 (0.2606)	**0.3565** (0.2734)	0.1741 (0.2734)
	PE	0.1258 (0.2606)	0.1875 (0.2606)	0.1734 (0.2606)	**20.63** (0.2606)	**2.926** (0.2734)	**51.42** (0.2734)
DSP	IN	0.1039 (0.2423)	0.09593 (0.2423)	0.1932 (0.2423)	**0.2678** (0.2423)	**1.287** (0.2480)	**0.5389** (0.2480)
	PE	0.2131 (0.2423)	0.1593 (0.2423)	**0.2748** (0.2423)	**10.62** (0.2423)	**694.2** (0.2480)	**52.90** (0.2480)

The Table 1.5 shows that, for the two-parameter models, the *IN* values are less than the critical values for all model/dataset combinations, except for the Erto-Lanzotti/DSP combination. However, the *IN* for this model/dataset combination implies a deviation from the tangent plane less than 17% (rather than 14%). So, it can be considered negligible. Moreover, it's worth keeping in mind that the DSP dataset is a critical dataset. In contrast, the *IN* values for the Richards model exceed the critical values for each dataset, indicating that the solution locus departs significantly from linearity for this model with these datasets. This alone may be sufficient to induce a modeller to abandon this model for further consideration. Finally, the Weibull-type model has different behaviours depending on adopted dataset. In fact, the *IN* value for the Weibull-type/jet aircraft engine combination exceeds the critical value with a deviation from the tangent plane that is less than 19% (rather than 14%); the *IN* value for the Weibull-type/piston aircraft engine combination is less than the critical value; the *IN* value for the Weibull-type/DSP combination exceeds highly the critical value. With respect to the *PE* values, those for the logistic, the Gompertz and the log-logistic models are less than the critical values, except for the log-logistic/DSP combination. On the contrary, the Erto-Lanzotti, the Richards and the Weibull-type models exhibit high *PE* values for each dataset. However, as anticipated, the *PE* can often be reduced by a suitable model reparameterization. In fact, different *model functions*, that are different parameterizations, can be associated with the same *model*. In order to find a model function with a smaller *PE* value, we have to identify the parameter or parameters responsible for nonlinear behaviour. Since the *PE* value doesn't accomplish this task, we turned to different approaches.

1.3.2 The parameter bias

The parameter bias calculated using the method of Box (Ratkowsky, 1983) can help to indicate which parameter or parameters are responsible for the departure from linear behaviour. In fact, the bias expressed as a percentage of the LS estimate (*percentage bias*) is a useful quantity as an absolute value in excess of 1% appears to be a good rule of thumb for indicating nonlinear behaviour. The absolute values of the percentage bias for each model/dataset combination are reported in Table 1.6.

The bold values point out the parameters for which the absolute value of percentage bias is considerably in excess of 1% .

Table 1.6 The absolute values of the percentage bias for each model/dataset combination

Data	Param.	Logistic	Gompertz	Log-logistic	Erto-Lanzotti	Richards	Weibull-type
Jet aircraft engines	α	1.043	1.326	1.514		**59.25**	0.2791
	k	1.034	1.237	1.501	**118.7**	**57.98**	**353.1**
	s				0.9808	**62.81**	**2.332**
Piston aircraft engines	α	0.4005	0.7908	0.8086		**7.204**	0.1069
	k	0.3901	0.6831	0.7964	**30.07**	**6.812**	**65.95**
	s				0.3891	**8.894**	0.6408
DSP	α	1.007	0.8593	1.593		**1051**	**3.480**
	k	1.178	0.8860	1.871	**28.21**	**193.0**	**138.5**
	s				**3.424**	**461.5**	**10.09**

The Table 1.6 shows that for the logistic, the Gompertz and the log-logistic models, the bias values are less or only slightly more than 1% . This suggests that the nonlinear behaviour of these models can be small in practical terms. In contrast, in accordance with the high values of their *PE*, the other models show very high percentage biases for some parameters. In particular, for the Erto-Lanzotti and Weibull-type models, most of the *PE* is centred in a single parameter (k), suggesting that much of the nonlinearity can be removed by a suitable reparameterization involving it. The situation with the Richards model is more difficult since all of its parameters contribute substantially to the overall nonlinear behaviour. However, the percentage biases are just a useful guide. On the contrary, a simulation study can fully settle the question (Ratkowsky, 1983).

1.3.3 Simulation studies

A simulation study can reveal the full extent of the non-normal behaviour of the LS estimators and possibly suggest useful reparameterizations (Ratkowsky, 1983).

The above analysis shows that the *PE* of the Erto-Lanzotti and the Weibull-type models can be reduced by a reparameterization involving the parameter k . However, we analyzed only the Erto-Lanzotti model. In fact, both models are flexible, but the Weibull-type model has one more parameter than the Erto-Lanzotti model. Moreover, the Weibull-type model can be converted in the Erto-Lanzotti model by the transformation $\alpha = P_{\lim} - P_0$. Therefore, we preferred the Erto-Lanzotti model to the Weibull-type one.

So, in order to find a better parameterization for the Erto-Lanzotti model, 1000 pseudo-random datasets were generated for each original dataset. In fact, an error term, ε (that is a random variable generated to be stochastically independent and identically normally distributed with zero mean and constant variance σ^2), was added to the Erto-Lanzotti model. The “true” values of the parameters k and s and of the error variance σ^2 were taken to be the quantities obtained from the LS fit to the original datasets (Ratkowsky, 1983). Each set of simulated data was then fitted by LS in order to examine the distributional properties of the LS estimators. The histograms of the standardized results for $\hat{k}$ are reported in Figure 1.5.

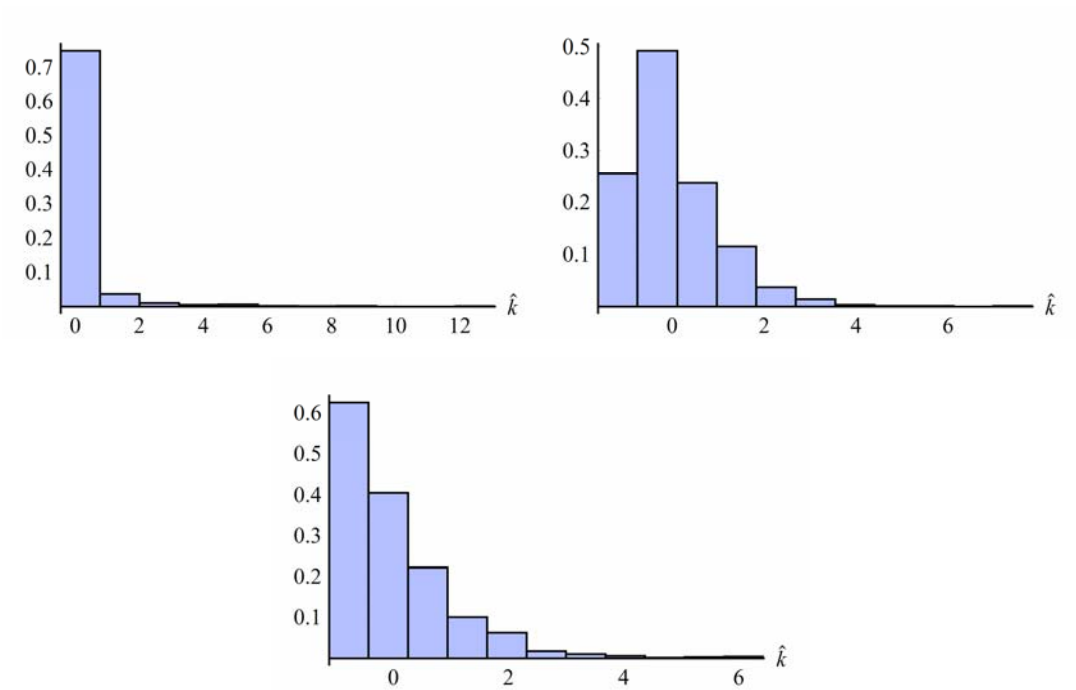


Figure 1.5. The histograms of the standardized results for $\hat{k}$ for jet aircraft engine, piston aircraft engine and DSP datasets, respectively

The Table 1.7 summarizes the values of skewness and excess kurtosis for each distribution of $\hat{k}$. It shows that the normality hypothesis is rejected with p-values less than 0.01.

Table 1.7 The skewness and excess kurtosis values and the test hypothesis results about them for each distribution of $\hat{k}$

Data	Measures	Values	u^*	*p*-values
Jet aircraft engines	Skewness	5.98	77.2	< 0.01
	Excess Kurtosis	50.4	325	< 0.01
Piston aircraft engines	Skewness	1.69	21.9	< 0.01
	Excess Kurtosis	5.93	38.3	< 0.01
DSP	Skewness	2.06	26.5	< 0.01
	Excess Kurtosis	6.52	42.1	< 0.01

Moreover, the Figure 1.5 shows histograms with a long right-hand tail that is typical of a lognormal distribution. This suggests that the Erto-Lanzotti model can be improved by replacing k by $e^{k'}$ (where e represents the base of the natural logarithm). In particular, since $\hat{k}$ is less than unity for each original dataset, we use $e^{-k'}$, so that the values of $\hat{k}'$ in the new parameterization shall be positive. Thus the new model function to be considered is as follows:

$$P(t) = P_0 + (1 - e^{-e^{-k'}t^s})(P_{\lim} - P_0) \tag{1.1}$$

The percentage bias (for the parameters k and k') and the *PE* for all the combinations of the new Erto-Lanzotti model function in (1.1) with the three datasets were calculated and compared with the ones concerning the original Erto-Lanzotti model function. The results are reported in Table 1.8.

Table 1.8 Percentage biases and *PE* for the Erto-Lanzotti model and the reparameterized Erto-Lanzotti model

Data	Measures	Erto-Lanzotti	Reparameterized Erto-Lanzotti
Jet aircraft engines	Percentage bias	118.7 (k)	0.9752 (k')
	PE	44.90 (0.2537)	0.1821 (0.2537)
Piston aircraft engines	Percentage bias	30.07 (k)	0.3868 (k')
	PE	20.63 (0.2606)	0.1220 (0.2606)
DSP	Percentage bias	28.21 (k)	2.812 (k')
	PE	10.62 (0.2423)	0.4165 (0.2423)

The Table 1.8 shows that the percentage bias and the *PE* are substantially reduced for each dataset. Although the nonlinear behaviour is still statistically significance for the DSP dataset, the new model function (1.1) is absolutely closer to linearity than the original one. The 1000 estimates $\hat{k}$ were converted into 1000 estimates $\hat{k}'$ via the function $\hat{k}' = \log\left(\frac{1}{\hat{k}}\right)$. Then, the histograms of the standardized results for $\hat{k}'$ are reported in the Figure 1.6.

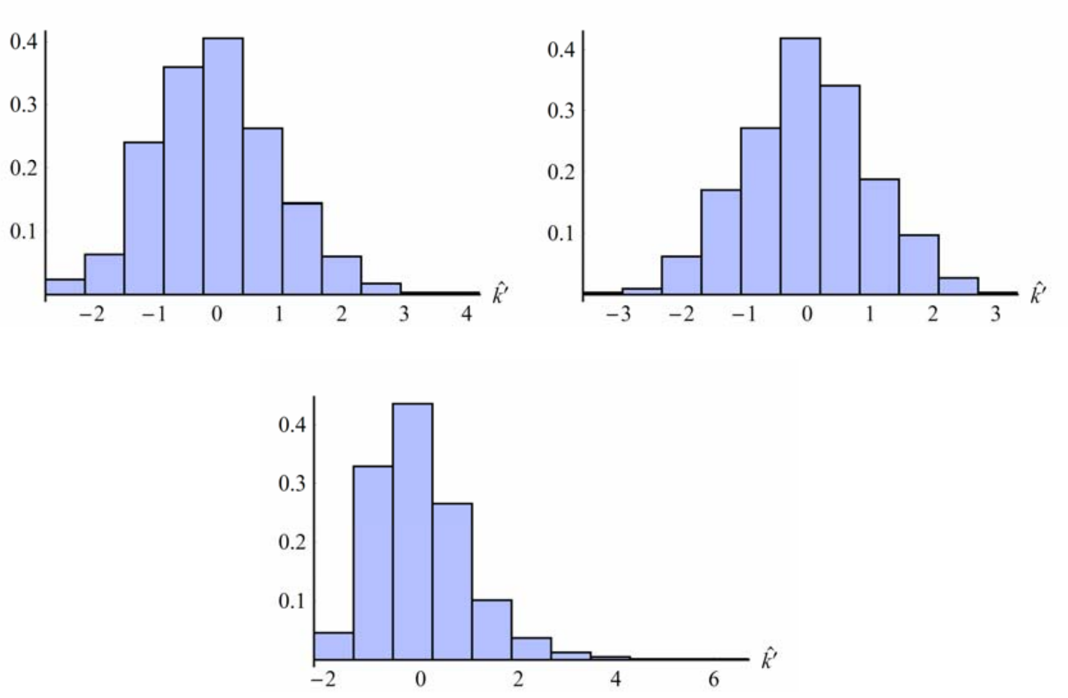


Figure 1.6. The histograms of the standardized results for $\hat{k}'$ for jet aircraft engine, piston aircraft engine and DSP datasets, respectively

The Figure 1.6 shows histograms much closer to a normal distribution than the previous ones. Moreover, the Table 1.9 summarizes the values of skewness and excess kurtosis for each distribution of $\hat{k}'$. The skewness and excess kurtosis values confirm a distribution closer to normal than the previous one (see Table 1.7), even if the normality hypothesis is still rejected for the jet aircraft engine and DSP datasets.

Table 1.9 The skewness and excess kurtosis values and the test hypothesis results about them for each distribution of $\hat{k}'$

Data	**Measures**	**Values**	u^*	***p*-values**
Jet aircraft engines	Skewness	0.319	4.12	< 0.01
	Excess Kurtosis	0.350	2.26	< 0.05
Piston aircraft engines	Skewness	0.013	0.168	> 0.05
	Excess Kurtosis	-0.0713	-0.460	> 0.05
DSP	Skewness	1.26	16.3	< 0.01
DSP	Excess Kurtosis	3.94	25.5	< 0.01

1.3.4 *Confidence regions for the parameters*

In order to confirm the nonlinearity reduction due to the reparameterization, the contours of the confidence regions for the parameters at the significance levels 90%, 95% and 99% of the Erto-Lanzotti model and the reparameterized Erto-Lanzotti model for each dataset are shown in the Figure 1.7.

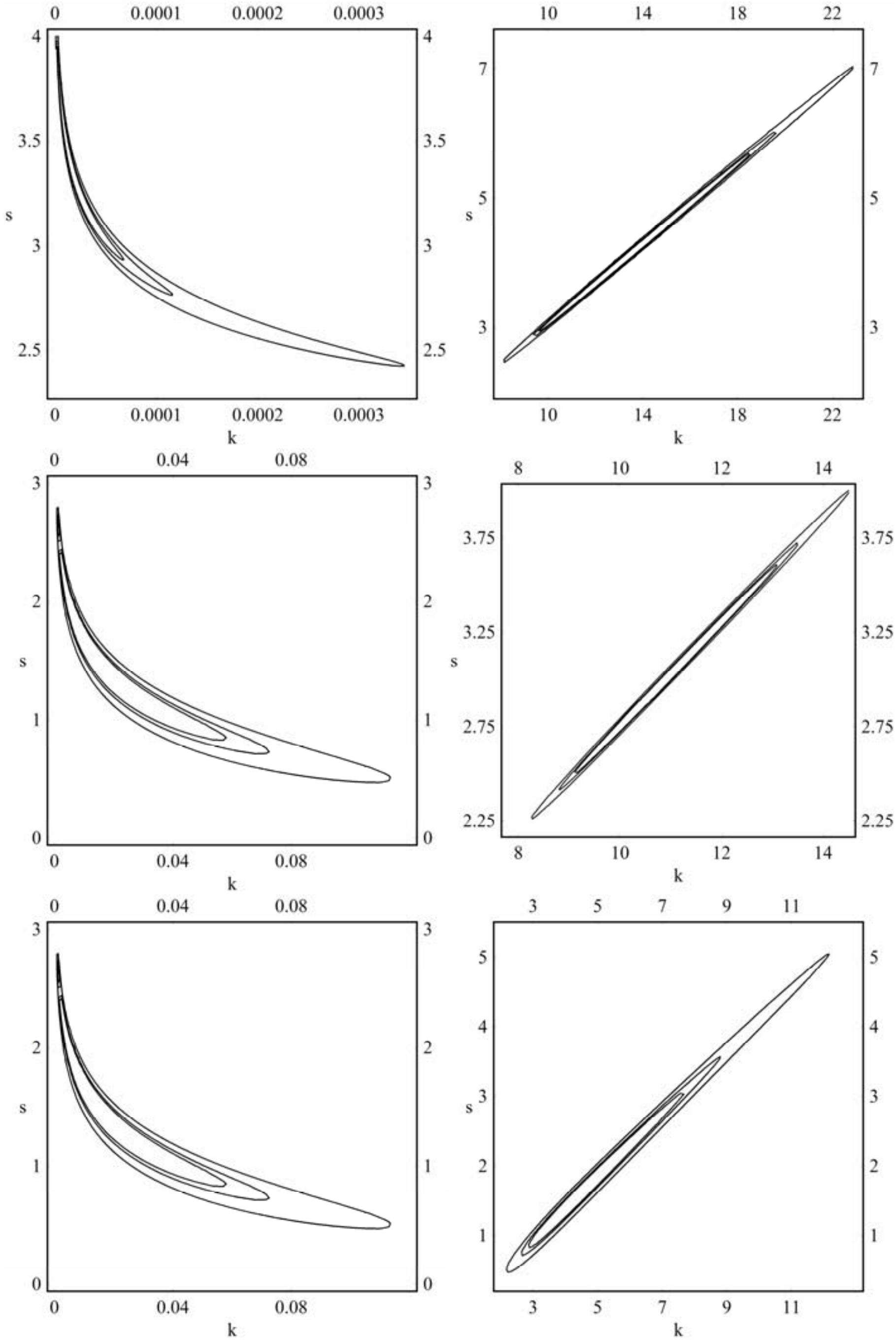


Figure 1.7. Confidence regions for the parameters of the Erto-Lanzotti model and the reparameterized Erto-Lanzotti model for jet aircraft engine, piston aircraft engine and DSP datasets, respectively

In fact, the extent to which these contours depart from an ellipse (the condition for a linear model) provides a visual picture of the degree of nonlinearity in the model (Draper & Smith, 1981; Ratwosky, 1983). Therefore, the closeness of the contours of the reparameterized Erto-Lanzotti model to an ellipse is a further proof of the nonlinearity reduction due to the reparameterization.

1.4. Conclusions

This work explores the development, the assumptions and the behaviour of some representative S-curve models in order to analyze the technological performance growth. The aim of the work was to present a comparative study of these models in order to create a better understanding of them aimed at making easier the selection of the appropriate model.

Obviously, caution should be exercised in generalizing the results of this study, since so few datasets were included. However, it is tempting to recommend the Erto-Lanzotti model in the model function (1.1) as the first choice to be considered for technological performance growth modelling. In fact, the model (1.1) is a flexible model even having only two parameters and is close to linear for the analyzed representative datasets. Moreover, it is the only model that derives from the identification of the main forces that rule the technological innovation process and that incorporates explicitly the original value of the technological performance level, P_0.

Chapter 2 Modelling the Dynamics of Technological Innovation

2.1. Introduction

The role of technological evolution and innovation in shaping the destinies of industries and companies is often underestimated. Technological change is a key factor as both a creative force in the growth of companies and as a destructive force making those same companies vulnerable to competition. Generally, in any market, there are periods of continuity, when the rate of innovation is incremental and major changes are infrequent, and periods of discontinuity, when major product or process changes occur (see Chapter 4). In particular, when an invading technology appears, the established technology generally offers better performance or cost than the challenger, which is still unperfected. Therefore, the new technology may be viewed as crude, leading to believe that it will find only limited application. However, the performance superiority of the established technology may prevail for some time, but if the new technology has real merit, it typically enters a period of rapid improvement, just as the established technology enters a stage of slow incremental improvements. Nevertheless, successful companies tend to be remarkably creative in defending their old technologies, which often reach unimagined heights of elegance in design and technical performance only when their demise is clearly predictable (Utterback, 1994).

Thus, two main forces play a leading role in starting a technological innovation process. The first force is the inertia of the companies toward change process. The second force is the stimulus toward the improvement process. This stimulus originates from the difference between the expectation and the perception of the offered performance level (D’Avino & Erto, 2006). In order to statistically understand the dynamics of technological innovation process, we propose the concept of “force of change”. Then, we formulate a new flexible S-curve model and we evaluate its genesis and its statistical-mathematical properties.

2.2. The cyclical model of technological change of Abernathy and Utterback

In a series of articles published from the mid to late-1970s, Abernathy and Utterback (1978) laid out a model of the dynamics of innovation. Subsequently, many studies concerning different industries supported their hypotheses. The Abernathy and Utterback model hypothesizes that the rate of innovation for both products and processes follows a general pattern over time. In particular, they proposed a cyclical model of technological change in which an industry evolves through long periods of incremental change punctuated by technological discontinuities (or discontinuous innovations that redefine trajectories of product or process performance). Examples of product discontinuities include jet (vs. piston) engines, diesel (vs. steam) locomotives and integrated circuits (vs. discrete transistors) (Tushman & Anderson, 1986). Examples of process discontinuities include the flat-glass and cement industries (Anderson & Tushman, 1990). The introduction of these radical innovations gives rise to an era of experimentation as companies struggle to absorb or destroy the innovative technology (*era of ferment*). In fact, the era of ferment is characterized by a high rate of variation – owing to a lack of common understanding among technical experts about how the new technology operates and where its economic performance limits lie – followed by a selection process. For example, in the early years of the automobile industry, fundamental questions such as whether the power source should be a steam-, electric-, or gasoline-powered engine were not yet resolved. Moreover, we are living an era of ferment right now. In fact, there could be a change in the way cars and trucks are powered. The auto companies are moving forward on alternatives to internal combustion engine vehicles, but the intellectual and physical barriers are still high. On the other hand, it may just be that political and/or legal issues will be the main drivers of change process (Vasilash, 2000).

Subsequently, the selection process culminates in a *dominant design* by a retention mechanism of the successful variation. In particular, a dominant design is a single architecture that establishes dominance in a product or process class. In fact, it meets with general acceptance, even if it is not necessarily the optimal design. Therefore, dominant designs permit companies to design standardized and interchangeable parts and to optimize organizational processes for volume and efficiency. So, once a design becomes an industry standard, it is difficult to dislodge it because it creates economies due to learning by doing. Examples of dominant designs are the internal combustion engine, the IBM personal computer, the Ford Model T automobile and the Douglas DC-3 aircraft.

After a dominant design emerges, technological progress is driven by numerous *incremental innovations* (innovations that reinforce established trajectories of product or process performance) and the rate of technological innovation declines markedly (*era of incremental change*). In fact, the focus of competition shifts from higher performance to lower cost and to differentiation via minor design variations and strategic positioning tactics. Finally, this period is broken by the next technological discontinuity (Anderson & Tushman, 1990; Suárez & Utterback, 1995).

2.3. The “force of obsolescence” or “force of change”

In order to model the dynamics of innovation, we can reformulate the index “force of obsolescence”. It was proposed by Erto & Lanzotti (1995) and measures the local tendency toward obsolescence of the adopted technology. In particular, the index “force of obsolescence” is so-defined:

$$r(t) = \frac{\frac{dP(t)}{dt}}{P_{\lim} - P(t)} = \frac{p(t)}{P_{\lim} - P(t)} \qquad (2.1)$$

where $p(t)$, being the derivative of $P(t)$, is defined density of obsolescence. The density of obsolescence gives, for every t, the growth rate of obsolescence, that is the growth rate of the technological performance level toward its saturation value. The force of obsolescence measures the density of obsolescence, using as unity the distance of the current performance level of the adopted technology from its saturation value. So, it is a local (*i.e.* at moment, instantaneous) measure of the tendency toward the obsolescence of the adopted technology. In other words, the force of obsolescence measures the speed toward obsolescence that the adopted technology assumes conditionally to its age. The higher this speed the smaller the time to the end of the improvement process. Therefore, it represents the mathematical formulation of the incentive to substitute the adopted technology. In this context, the index (2.1) will be called “force of change” (D’Avino & Erto, 2006).

In particular, following the cyclical model of technological change of Abernathy and Utterback (1978), the force of change should be an increasing function during the initial period of product or process design ferment (era of ferment). Subsequently, it should exhibit a maximum point when a dominant design emerges. In fact, the dominant design reduces variation and uncertainty in the product or process class. Therefore, the maximum point represents the “instant” when the selection process culminates in a dominant design that becomes well understood and established. Finally, the force of change should become a decreasing function during the era of incremental change since a retention mechanism of the dominant design occurs. In fact, 80% of all progress within a technological change cumulates during the era of ferment (Anderson & Tushman, 1990). Obviously, dominant designs don’t remain dominant for ever. The force of change begins to increase again and the cycle of technological change repeats itself when the next technological discontinuity appears.

The index (2.1) is useful to discriminate between different models of S-curves too. In fact, little differences in the shape of S-curves assume greater evidence in the shape of force of change. Therefore, it constitutes a further item to be considered in the choice of the appropriate S-curve model. The forces of change of the models presented in the Chapter 1 were formulated and reported in the Table 2.1.

Table 2.1. The forces of change of the compared S-curve models

Model	Force of Change
Logistic	$r(t)=\dfrac{k}{1+e^{\alpha-kt}}$ $\quad \lim_{t\to+\infty} r(t)=k$
Gompertz	$r(t)=\dfrac{ke^{\alpha-kt}}{e^{e^{\alpha-kt}}-1}$ $\quad \lim_{t\to+\infty} r(t)=k$
Log-logistic	$r(t)=\dfrac{k}{t(1+e^{\alpha-k\ln t})}$ $\quad \lim_{t\to+\infty} r(t)=0$
Erto-Lanzotti	$r(t)=kst^{s-1}$ $\quad \lim_{t\to+\infty} r(t)=+\infty$
Richards	$r(t)=\dfrac{ke^{\alpha-kt}}{s(1+e^{\alpha-kt})\left((1+e^{\alpha-kt})^{1/s}-1\right)}$ $\quad \lim_{t\to+\infty} r(t)=k$
Weibull-type	$r(t)=kst^{s-1}$ $\quad \lim_{t\to+\infty} r(t)=+\infty$

The Table 2.1 shows three different patterns of the index $r(t)$. In particular, the force of change of the log-logistic model is an increasing function at the beginning and, then, exhibits a maximum point and decreases toward zero as $t\to+\infty$. Therefore, it fits well the cyclical model of technological change of Abernathy and Utterback (1978).

On the other hand, the logistic, the Gompertz and the Richards models show a force of change that tends to a constant k as $t\to+\infty$. This pattern of $r(t)$ can represent a context in which equilibrium is reached between two opposing sets of forces: the driving forces, that seek to promote change, and the restraining forces, that attempt to maintain the status quo. In fact, in the innovation management context, the exploitation and exploration activities are in constant tension (Fosfuri & Ronde, 2006). On the one hand, the exploitation of the current technology might generate structural inertia and reduce a company's ability to adapt to future environmental changes and opportunities. On the other hand, exploring new alternatives might disrupt successful routines. For example, the implementation of a successful innovation, backed by an R&D department, results costly changes for a production department. In response, the production department tries to improve the current technology in an attempt to convince the management not to implement the innovation. In this context, Foster (1986) describes the case of DuPont and its decision in the 1950s to move from the established nylon technology to the new polyester technology for the production of car tires. Behind the decision there was a conflict between production engineers at the nylon plant and researchers supporting the new technology. The production engineers managed to push the nylon technology to the limits, and provided sufficient evidence to convince the management that the nylon technology would remain competitive. The polyester technology was eventually shelved. Obviously, the equilibrium can be raised or lowered by changes in the relationship between the driving and the restraining forces.

Finally, the Erto-Lanzotti and the Weibull-type models exhibit a force of change that tends to infinity as $t \to +\infty$. This pattern of $r(t)$ can represent a very competitive market where, despite settling on a dominant design, innovation still occurs, albeit of a different character. For example, in the mobile phone market the innovations on the system level (e.g. infrastructure, technological standards) were followed by a flurry of additional features (e.g. games, ringtones, vibration alert, memory location, multimedia messaging, camera, handset design, etc.) since mid-1990s. In particular, a typical mobile phone user is likely to be more interested in the features and capabilities of a handset he buys than its technological details. Therefore, it is of paramount importance that the mobile phone companies look at innovation in handsets from the user’s point of view. In fact, unlike for PCs, there is no standard user interface in the mobile industry. Therefore, the design of the user interface can determine not only the success of an individual model but also that of subsequent models. In fact, the mobile phones are also fashion items. Consequently, manufacturers of mobile phones compete on product differentiation by introducing new product features continuously (Koski & Kretschmer, 2006).

Figure 2.1 shows the three different patterns of the force of change.

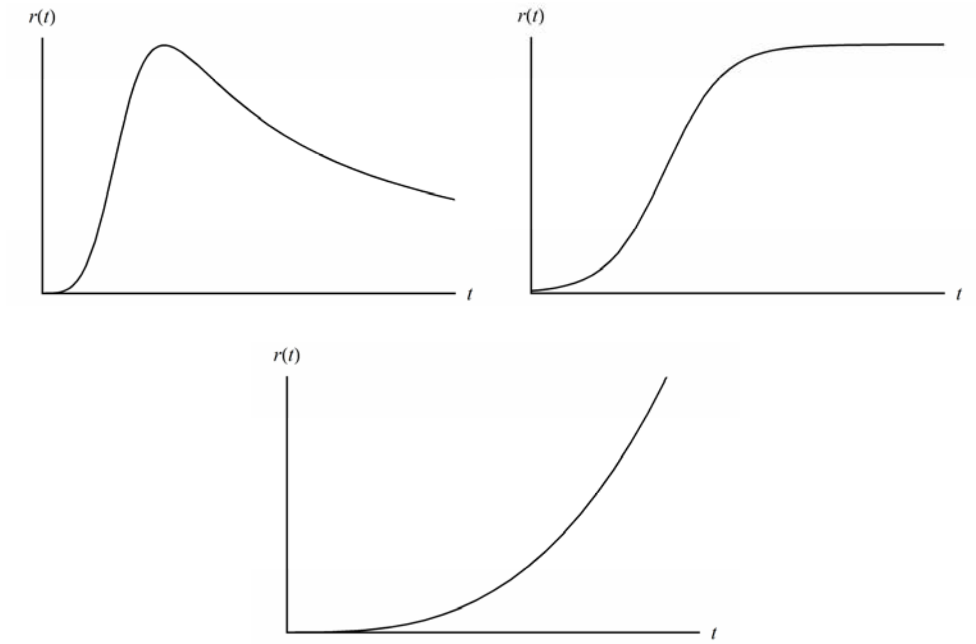


Figure 2.1. The different patterns of the force of change

2.4. A flexible s-curve model

From the above analysis, it emerges that only the log-logistic model fits well the pattern of force of change in according to the cyclical model of technological change of Abernathy and Utterback (1978). On the other hand, the log-logistic model doesn't show optimal mathematical properties. Therefore, we propose a new flexible S-curve model with the same $r(t)$ pattern.

2.4.1 Genesis of the model

The genesis of the model is directly linked to the functional form of $r(t)$. In fact, given it, the S-curve model can be easily determined. Moreover, it is assumed that

$$\lim_{t \to 0} P(t) = P_0 \qquad \lim_{t \to \infty} P(t) = P_{\lim} \tag{2.2}$$

In particular, in order to obtain the desired pattern of force of change (a function that increases at the beginning and, then, exhibits a maximum point and decreases toward zero as $t \to +\infty$), we chose the following functional form of $r(t)$:

$$r(t) = \frac{st^{s-1}}{k^s + t^s} \qquad k > 0;\ s > 1 \tag{2.3}$$

Now, it follows from (2.1) that

$$r(t)dt = \frac{dP(t)}{P_{\lim} - P(t)}$$

or

$$\int_0^t r(t)dt = \{-\log[P_{\lim} - P(t)]\}_0^t .$$

Thus,

$$\log \frac{P_{\lim} - P(t)}{P_{\lim} - P_0} = -\int_0^t r(t)dt$$

or

$$\frac{P_{\lim} - P(t)}{P_{\lim} - P_0} = e^{-\int_0^t r(t)dt} = \frac{k^s}{k^s + t^s} .$$

Finally, we obtained the following S-curve model:

$$P(t) = P_0 + \left(1 - \frac{k^s}{k^s + t^s}\right)\left(P_{\lim} - P_0\right) \qquad k > 0;\ s > 1 \tag{2.4}$$

2.4.2 The statistical-mathematical properties of the model

The model (2.4) is a flexible two-parameter model. In fact, the inflection point coordinates are:

$$t^* = k\left(\frac{s-1}{s+1}\right)^{\frac{1}{s}} \qquad P(t^*) = P_0 + \left(\frac{s-1}{2s}\right)\left(P_{\lim} - P_0\right) \tag{2.5}$$

Therefore, it can offer wide variations in the degree of symmetry for a given inflection point. Moreover, it assumes an original level of the technological performance (P_0) explicitly.

The closeness to linear behaviour of the model (2.4) was also evaluated by fitting it to real datasets presented in the Chapter 1. First, we calculated the curvature measures of Bates and Watts (1980). The results are reported in Table 2.2 with the critical values in brackets. The bold values point out the curvature measures that exceed the critical values.

Table 2.2 The curvature measures of Bates and Watts and the critical values for each model/dataset combination

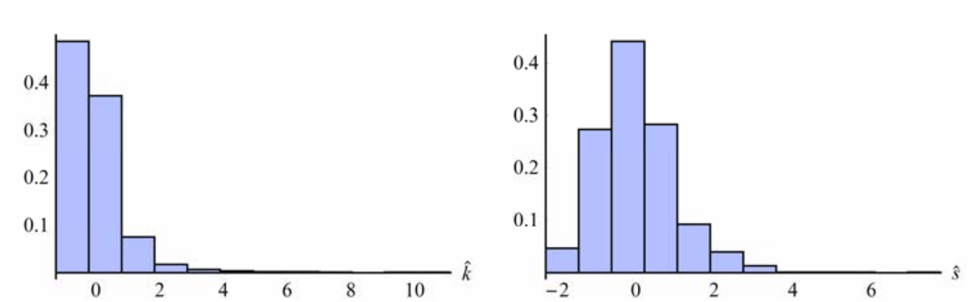
Data	**Curvature measures**	**Model (2.4)**
Jet aircraft engines	IN	0.1609 (0.2537)
	PE	0.2470 (0.2537)
Piston aircraft engines	IN	0.1656 (0.2606)
	PE	0.1856 (0.2606)
DSP	IN	**0.2736** (0.2423)
	PE	**1.9603** (0.2423)

The Table 2.2 shows that the *IN* and *PE* of the model (2.4) are less than the critical values for the jet aircraft engine and piston aircraft engine datasets. However, the *IN* for the DSP dataset implies a deviation from the tangent plane less than 18% (rather than 14%). So, it can be considered negligible. Moreover, it's worth keeping in mind that the DSP dataset is a critical dataset (see Chapter 1). On the other hand, for this dataset the *PE* value is high too. Therefore, we searched for a better parameterization for the model. In order to identify the parameter or parameters responsible for nonlinear behaviour, we calculated the parameter bias. The Table 2.3 summarizes the results. The bold values point out the parameters for which the absolute value of percentage bias is considerably in excess of 1% .

Table 2.3 The absolute values of the percentage bias for each model/dataset combination

Data	**Param.**	**Model (2.4)**
Jet aircraft engines	k	0.02891
	s	1.574
Piston aircraft engines	k	0.02031
	s	0.7745
DSP	k	**3.213**
	s	**3.500**

In accordance with the higher value of *PE*, the parameter percentage biases for the DSP dataset are higher than the other ones. Moreover, both parameters contribute substantially to the nonlinear behaviour. Therefore, we turned to a simulation study in order to reveal the full extent of the non-normal behaviour of the LS estimators. The histograms of the standardized results for $\hat{k}$ and $\hat{s}$ for DSP dataset are reported in Figure 2.2.



Figures 2.2. The histograms of the standardized results for $\hat{k}$ and $\hat{s}$ for DSP dataset

The Table 2.4 summarizes the values of skewness and excess kurtosis for each above distribution. It shows that the normality hypothesis is rejected with p-values less than 0.01 (Ratkowsky, 1983).

Table 2.4 The skewness and excess kurtosis values and the test hypothesis results about them for the distributions of $\hat{k}$ and $\hat{s}$

Data	**Measures**	**Param.**	**Values**	u^*	***p*-values**
DSP	Skewness	k	4.25	54.8	< 0.01
		s	1.24	16.0	< 0.01
	Excess Kurtosis	k	29.3	189	< 0.01
		s	4.32	27.9	< 0.01

Moreover, the Figure 2.2 shows histograms with a long right-hand tail that is typical of a lognormal distribution. This suggests that the model (2.4) can be improved by replacing k by $e^{k'}$ and s by $e^{s'}$ (where e represents the base of the natural logarithm). Thus the new model function to be considered is as follows:

$$P(t) = P_0 + \left(1 - \frac{e^{k e^{s}}}{e^{k e^{s}} + t^{e^{s}}}\right)\left(P_{\lim} - P_0\right) \tag{2.6}$$

The percentage bias (for the parameters k and k' and the parameters s and s') and the *PE* for the combination of the new model function in (2.6) with the DSP dataset were calculated and compared with the ones concerning the original model function in (2.4). The results are reported in Table 2.5.

Table 2.5 Percentage biases and *PE* curvature for the both model functions

Data	Measures	Model (2.4)	Model (2.6)
DSP	Percentage bias	3.213 (k)	0.8160 (k')
		3.500 (s)	0.1989 (s')
	PE	1.9603 (0.2423)	0.9310 (0.2423)

The Table 2.5 shows that, even if the percentage bias of $\hat{k}$ and $\hat{s}$ is substantially reduced, the *PE* is reduced only by a relatively small amount which is not sufficient to make the nonlinearity not significant statistically. Therefore, it appears that the less complicated model function (2.4) might be adequate for most purposes, since it is close to linear for the jet aircraft engine and piston aircraft engine datasets and shows a no drastic departure from linearity for DSP dataset.

2.5. Conclusions

In this work the dynamics of technological innovation process were analyzed. In particular, the "force of change" index allowed the modelling of different representative scenarios. Moreover, it constitutes a further item to be considered in the comparative study amongst the S-curve models presented in the Chapter 1. Finally, a new S-curve model with a specific pattern of force of change was proposed and its good statistical-mathematical properties were evaluated.

Chapter 3 S-curve Model as Benchmarking and Self-Assessment Tool

3.1. Introduction

The unit of analysis in most published studies of technological growth has been at the industry level (for example, see McGrath, 1998; Nieto *et al.*, 1998). In this context, the S-curve model is a useful framework in order to describe the technological innovation process. Consequently, some authors have advocated the use of the S-curves at the company-level (Becker & Speltz, 1983; Foster, 1986). On the other hand, they have not addressed how managers might use it as a guide in the strategic management of technology. Therefore, the S-curve analysis as a basis to plan new technology developments at the company level shows some shortcomings. In fact, S-curves seem less relevant to performance of assembled products than to performance of the components, since, in the design of most assembled products, there is more than one route to achieve performance improvement. Therefore, the levels at which individual companies perceive the saturation value of the technological performance differ amongst them depending on company-specific characteristics of product design. This suggests that managers may have substantial leeway for extending the performance of the adopted technology before undertaking the risk and expense of developing different technological approaches (Christensen, 1992a; Christensen 1992b). Moreover, in the practical use of S-curves, problems arise from both choosing the performance indicator and from identifying the saturation value of the performance level. The choice of performance indicator depends on the business area as well as on the specific product/service offered. It must reflect some characteristics which are easily measurable and, at the same time, recognizable by clients (for example, market share, technical or financial performance, productivity of key resources or other); it must be relevant from both technical and business perspective and it must reflect the fact that the technology is less costly, more attractive to potential buyers, or in some way more profitable. In particular, the performance indicator must reflect the improvements of the products that incorporate the technology (quality, security, cost, etc.) (Asthana, 1995; Dervitsiotis, 2005; Foster, 1986). Then, the saturation value of the performance level must be performed on the basis of physical and/or commercial constraints (Erto, 1997a; Erto & Lanzotti, 1995, Nieto *et al*., 1998; Ratwosky, 1990).

Christensen (1992b) argues that the benchmarking against competitors' performance, in addition to the own historical performance and perceived natural limits, may provide a clearer view of the potential improvement of the adopted technology. In fact, the benchmarking can help to identify the performance indicator and, above all, its saturation value when there are wide differences of opinion about it amongst companies. In particular, the disagreement occurs when the technological performance results from exploiting some combination of broadly understood physical laws and experience-based know-how of the specific company. Obviously, the saturation value may in practice be a moving target rather than immovable barrier, since nobody knows what researchers may discover or develop in the future (Christensen 1992a; Christensen, 1992b; Christensen, 1997). However, the reference to the technological leader is a good starting point.

In this work, we propose the S-curve itself as a benchmarking (against the leader company in the industry) and self-assessment tool.

3.2. S-curve as benchmarking tool

Benchmarking is a technique used in strategic management which allows companies to evaluate various aspects of their processes in relation to best practice within their industry with the aim of increasing some aspects of performance.

For these purposes, the top management can employ the S-curve assuming the leader company (which adopts the same technology) in the industry as the reference model (Corti, 2002). In fact, the S-curve of this company represents the "performance borderline" that is the locus of the maximum performance growth reachable through the adopted technology. In this way, a company which adopts a specific technology with delay, or adopts it improperly, will accumulate both a "performance delay", said x, and a "performance distance", said y, against the leader company (D'Avino & Erto, 2007a) (Figure 3.1). Therefore, the monitoring of both x and y can be useful in the strategic decision-making process within company by alerting the management to the remedial actions. In particular, the company could decide to invest further resources to accelerate its technological growth (evolutionary improvement process) or to use a new technology since the old one doesn't provide the desired results anymore (radical improvement process). Moreover, it's interesting to note that also the leader company can exploit these results. In fact, the reactive behaviour of the monitored companies must induce the leader one to adopt a new technology before the others achieve its technological performance level (Corti, 2002).

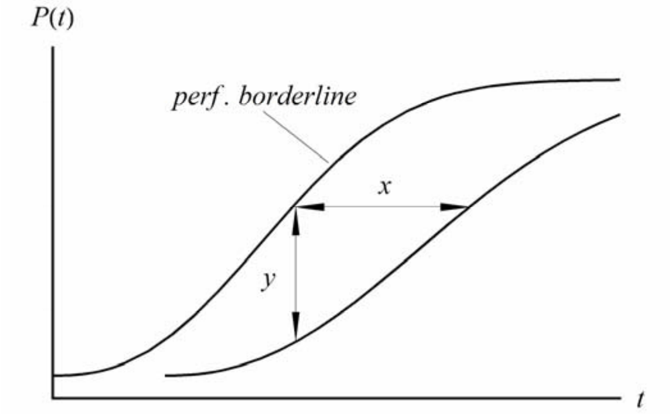


Figure 3.1. "Performance Delay" and "Performance Distance" against "Performance Borderline"

3.2.1 Reactivity functions: Density of Hope of End Delay and Density of Hope of End Distance

Based on the proposed tool, we can reformulate an operative function proposed in a different context (Erto, 1997b) using it to evaluate the reactivity of the company against accumulated delays and distances. In this way, we obtain two functions, the "*Hope of End Delay*" (HEDE) and the "*Hope of End Distance*" (HEDI), so defined:

$$HEDE(x,\Delta x) = \frac{F_X(x+\Delta x) - F_X(x)}{1 - F_X(x)}$$
$$\tag{3.1}$$
$$HEDI(y,\Delta y) = \frac{F_Y(y+\Delta y) - F_Y(y)}{1 - F_Y(y)}$$

being $F_X(x)$ and $F_Y(y)$ the probability distribution functions respectively of the random delay, x, and the random distance, y. They both measure a conditional probability, since the numerator measures the probability that the delay (or distance), x (or y), finishes between x and $x+\Delta x$ (or y and $y+\Delta y$), while the denominator measures the probability that the delay (or distance) is greater than x (or y).

However, for the practical use, rather than the HEDE and HEDI functions, it is more effective to consider the functions "*Density of Hope of End Delay*" (DHEDE) (Erto, 1997b) and "*Density of Hope of End Distance*" (DHEDI), so defined:

$$DHEDE(x) = \lim_{\Delta x \to 0} \frac{HEDE(x,\Delta x)}{\Delta x}$$
$$\tag{3.2}$$
$$DHEDI(y) = \lim_{\Delta y \to 0} \frac{HEDI(y,\Delta y)}{\Delta y}$$

The indexes (3.2) are very significant tools to assess the typical behaviours of the company operatively. In fact:

1. if the *DHEDE* (or *DHEDI*) is increasing, it means that the end of delay (or distance) is more frequent after long rather than short delays (or distances), *i.e.* the company is *robust* since its reaction improves more and more as delay (or distance) increases;
2. if the *DHEDE* (or *DHEDI*) is constant, it means that the end of delay (or distance) is independent from the delay (or distance) that has just occurred, *i.e.* the company is *apathetic* since it shows no reaction to delays (or distances);
3. if the *DHEDE* (or *DHEDI*) is decreasing, it means that the end of delay (or distance) is more frequent after short rather than long delays (or distances), *i.e.* the company is *weak* since its reaction is discouraged more and more as delay (or distance) increases.

3.2.2 *Applicative example*

In order to highlight the main features of the proposed tool and derived tools, we simulated a typical and widely representative scenario in which a company monitors the performance growth when a technology is adopted (Figure 3.2). Generally, this company begins to use the technology after the leader company. So, we simulated the initial delay to be equal to 5 years. It's interesting to note that the different S-curve slopes represent the different innovative capabilities of the two companies. In fact, the leader company is the fastest in achieving the saturation value of the adopted technology.

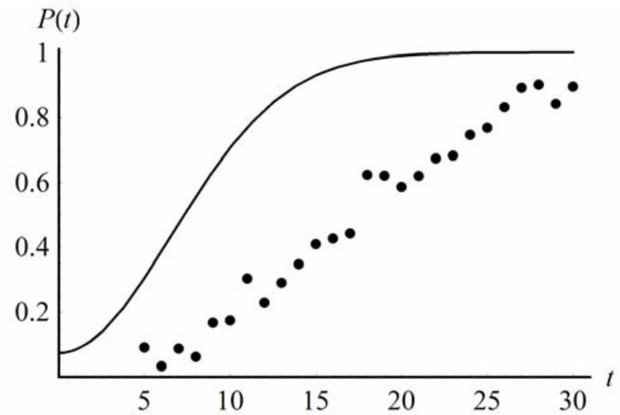


Figure 3.2. "Performance Borderline" and dataset of the monitored company

The continuous S-curve represents the "performance borderline" of the leader company and the dots represent the dataset of the technological performance levels, $P(t_i)$, gathered yearly by the monitored company. The company monitors the yearly accumulated "performance delays", x_i, and "performance distances", y_i, against the "performance borderline" (the continuous S-curve) over a period of 25 years. This period was considered a sufficient time to achieve the maturity of the adopted technology. In fact, in order to generate our dataset, an error term, ε (that is a random variable generated to be stochastically independent and identically normally distributed with zero mean and constant variance σ^2), was added to the Erto-Lanzotti model. The "true" values of the parameters k and s and of the error variance σ^2 were taken to be the quantities obtained from the LS fit to the DSP original dataset (see Chapter 1).

Using the following non parametric estimators, six point estimates of both *DHEDE* and *DHEDI* were obtained:

$$DHEDE(x_i) = \frac{\hat{f}_X(x_i)}{1-\hat{F}_X(x_i)} = \frac{n_{i+1}-n_i}{\Delta x_i (N+1-n_i)}$$

$$DHEDI(y_i) = \frac{\hat{f}_Y(y_i)}{1-\hat{F}_Y(y_i)} = \frac{m_{i+1}-m_i}{\Delta y_i (M+1-m_i)} \tag{3.3}$$

being

$$\hat{F}_X(x_i) = \frac{n_i}{N+1} \qquad \hat{F}_Y(y_i) = \frac{m_i}{M+1};$$

$$\hat{f}_X(x_i) = \frac{\hat{F}_X(x_{i+1}) - \hat{F}_X(x_i)}{x_{i+1}-x_i} = \frac{n_{i+1}-n_i}{(N+1)\Delta x_i}$$

$$\hat{f}_Y(y_i) = \frac{\hat{F}_Y(y_{i+1}) - \hat{F}_Y(y_i)}{y_{i+1}-y_i} = \frac{m_{i+1}-m_i}{(M+1)\Delta y_i}$$

N (or M) is the number of all registered delays (or distances);

n_i (or m_i) is the delay number less than or equal to x_i (or y_i).

Interpolating the six points both for *DHEDE* and *DHEDI*, the following functions were estimated:

$$DHEDE(x) = 0.089 + 2.1 \cdot 10^{-3} x^2 \qquad DHEDI(y) = -2.65 + 36.5y$$

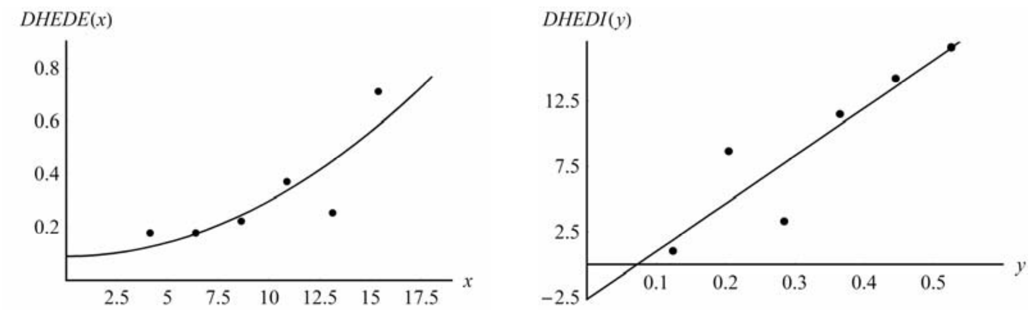


Figure 3.3. *DHEDE* and *DHEDI* estimated functions

The shapes of the *DHEDE* and *DHEDI* (Figure 3.3) suggest that the company is robust since its reaction improves more and more as both delay and distance increase. Moreover, the company is more reactive to “performance distance” than to "performance delay" since the slope of the *DHEDI* function is greater than the slope of the *DHEDE* function.

3.3. S-curve as self-assessment tool

Assessment is the process of evaluating an organization and its improvements, achievements and processes against a reference model for continuous improvement (Hillman, 1994). Therefore, the above proposed tool may be used by companies also in self-assessment with the aim of improving organizational performance. In fact, as well as the technological performance growth, the growth of a chosen performance parameter of any process of a company can be conformed to an S-curve pattern as a function of time (Dervitsiotis, 2003; Dervitsiotis, 2004; Dervitsiotis, 2005; Grove, 1999; Stockport, 2000).

Generally, companies implement the Quality Award Models, so called Business Excellence Models (the most famous are: the Deming Application Prize (DP), the Malcolm Baldrige National Quality Award (MBNQA) and the European Quality Award (EQA)) for self-assessment, but many of them, especially the small ones, are still dissatisfied with these practices (Rodríguez-Escobar *et al.*, 2006; Williams *et al.*, 2006). Consequently, the number of small companies which implement a formal quality management system or which develop self-assessment against the criteria of these business excellence models remains very low (Sturkenboom et al., 2001).

3.3.1 Small companies' experiences with self-assessment

Often quality management practices are seen as being important for large companies only, although there are many examples and there is enough research evidence to show that quality principles apply for small companies too. On the other hand, small companies find more difficulties in the implementation of formal practices due to the general lack of technical and specialist know-how in the field of quality combined with the high concentration of decision-making processes in the figure of the entrepreneur-owner (Biazzo, 2005). Therefore, many small companies tend to adopt formal quality systems only when there are significant external pressures to do so (Brown *et al.*, 1998).

Similarly, self-assessment practices are not very spread in small companies. In fact, self-assessment is perceived to be used only when applying for an award, which is seen like something addressed to large companies exclusively (Wilkes and Dale, 1998). Moreover, the business excellence models translation into self-assessment tools is generally seen as too complicated and time-consuming. In fact, their language is not easy to understand and considerable training is needed in relation to their implementation (Wilkes and Dale, 1998; Sturkenboom et al., 2001). Therefore, some authors modified the excellence models to suit them to small companies but the problems mentioned above were not solved (Sturkenboom et al., 2001). So, more needs to be done in terms of language simplification, format of the model and simplification of the application document (Wilkes and Dale, 1998).

3.3.2 Self-assessment tools

It's worth recognizing that the introduction of internationally respected quality awards has promoted quality awareness and provided a platform for sharing successful quality management initiatives (Lee and Quazi, 2000; Van der Wiele *et al*., 2000). Moreover, the quality awards have stimulated the use of self-assessment as a way of measuring progress on the quality journey and give direction to further improvement activities (Sturkenboom et al., 2001). These awards contain a number of criteria addressed toward many aspects of a company such as leadership, information analysis, process management, strategic planning, human resource management, partnership, public responsibility, quality results, operation results and customer satisfaction (Lee and Quazi, 2000; Samuelsson and Nilsson, 2001). The mode of assessment is the evaluation of a written application that the companies submit to a team of quality assessors. Subsequently, the quality assessors give back a thorough feedback on the relative strengths and weaknesses of the companies together with a numerical score for the application. This process is long and tedious. In fact, companies take many months to prepare for the application and each application may be about 80 to 100 pages long. Therefore, many companies give up unless they think they are prepared and have a real chance of winning the award (Lee and Quazi, 2000).

Moreover, since the self-assessment derived from awards uses tools born with different aims, specific approaches are needed today (Conti, 1997). In particular, the differences between award assessment and self-assessment are evident. In fact, award evaluations are third-party assessments since the body that conducts the assessment is external and independent from the company, while self-assessment is a first-party evaluation based on the complete and active participation of all people involved. Finally, since the goal of award assessment is to choose the best performers among a number of applicants, comparability by scoring is essential. On the contrary, the use of a score is a risk for the diagnostic power of self-assessment since experience has amply proved that managers tend to concentrate on scoring rather than on searching for the causes of problems (Conti, 1997).

In this context, the above proposed tool supports a self-assessment process independent from the Awards criteria. In fact, it shows the following main features:

1. It is not complex being not extensive and having a language easy to understand;
2. It is not time-consuming since it doesn’t require a long written documentation;
3. It focuses on processes instead of scoring;
4. It is a diagnostic tool for the continuous improvement.

3.4. Conclusions

In this work a new mathematical tool for benchmarking and self-assessment was proposed. This tool is original and it is a good starting point to overcome both the limits of the S-curves as a decision-making process guide at the company-level and the difficulties of the Quality Awards approach due to their complexity and subjective scoring system. Moreover, it allows the company to identify strengths and weaknesses in key technologies and/or processes and to monitor the impact of action plans.

Chapter 4 A Piecewise Regression Model for Sustainable Business Excellence

4.1. Introduction

Nowadays, organizational change has become a mandatory condition to survive in the marketplace for all companies. In fact, a business needs to be able to adapt to the changes of its external environment in order to remain competitive (Black & Crumley, 1997). In particular, since the late 1970s a number of change drivers, *i.e.* new technologies, new knowledge, new customer preferences, the deregulation of several industries and the increased globalization of trade, have caused an acceleration of environmental change (Dervitsiotis, 2003; Dervitsiotis, 2004). Such forces provide opportunities and challenges that drive companies through relatively long periods of stability punctuated by relatively short periods of turbulence. This environmental dynamism creates a set context or a set of conditions within which innovative ideas are fostered and developed (Carrillo & Gaimon, 2002; DeTienne & Koberg, 2002). In such a situation, companies are faced with big opportunities and big potential drawbacks. Those that are able to correctly foresee the future developments can gain a substantial competitive advantage (Borés *et al*., 2003). On the other hand, due to the rapid changes, entire business models can be rendered obsolete within a short time (DeTienne & Koberg, 2002; Hacklin *et al.*, 2004). As a consequence, a company's change strategy is of paramount importance to achieve sustainable growth and business excellence (Kanji, 2005). In fact, management approaches applicable in periods of stability are often quite inappropriate in periods of turbulence. Therefore, to achieve the key objectives in both stable and turbulent periods, management must develop the capability to operate in a dual management mode by shifting the criteria of success when environmental conditions demand it. This capability is called *Sustainable Business Excellence* (SBE) (Dervitsiotis, 2003; Dervitsiotis, 2004).

4.2. Discontinuous innovations

In this context, companies are highly dependent on innovation for competitive advantage and survival (DeTienne & Koberg, 2002). In fact, during the early nineties, between 60-70 per cent of the *Fortune* 100 largest global companies were found to not exist at all or in any form similar to what they were like in 1970 (Stockport, 2000). Therefore, many business school academics tried to identify the reasons of these failures. A typical example of the examined case studies is the history of the disk drive industry, where changes in technology, market structure, global scope and vertical integration have been very pervasive, rapid and unrelenting (Christensen, 1997). For this case, some scholars have attributed the high mortality rate to the unfathomable pace of technological change. On the contrary, a deeper study of the disk drive industry case history revealed that the different impact of technological change were at the root of the leading firms' failures. Two types of technological change were identified: the technological changes that *sustain* or reinforce established trajectories of product performance (*sustaining technologies*) by following an *incremental innovation* and the technological changes that *disrupt* or redefine performance trajectories (*disruptive technologies*) by following a *discontinuous innovation* (as anticipated in the Chapter 2). Incremental innovations and sustaining technologies were not sufficient for survival when new disruptive technologies were leapfrogging the price/performance parameters of these incremental innovations (Christensen, 1997; Kassicieh *et al.,* 2002).

Subsequently, some case studies showed that the technological change and the organizational change are closely connected. In fact, the impact of a technological change is often not limited to the new product's technological aspect, but it also requires changes of the company's operational and commercial activities through the reconfiguration of its business model (*e.g.* the introduction of automated teller machine changed banking, the introduction of computers in medical diagnosis changed medical care, etc.) (Calia *et al.*, 2007; Grove, 1999). On the basis of these experiences, discontinuous innovations change the framework in which the business operates, making obsolete the old ways. They permit entire industries and markets to emerge, transform or disappear, providing a significant competitive advantage. On the contrary, incremental innovations are minor changes (DeTienne & Koberg, 2002). Therefore, discontinuous innovations involve a higher degree of risk and uncertainty than incremental innovations, but they may mean an opportunity for a new period of growth (Grove, 1999). Unfortunately, history shows that, even though these are cataclysmic changes, successful companies often missed them. In fact, their leaders develop over time a confidence for the soundness of their success formula and "freeze" their structure and operating mode. This makes adaptation for survival difficult when the environment changes in significant ways (Dervitsiotis, 2003; Dervitsiotis, 2004). In particular, the first phase of organizational reaction to a discontinuous innovation is very often denial. An organizational change requires to get out of a comfort zone and tear up the organization, while management wants to perpetuate its successful past. Moreover, a transformation requires to re-start from a lower business level with very onerous consequences on the company. At the same time, companies that begin a decline as a result of a missed change rarely recover their previous greatness (Grove, 1997).

4.3. The strategic inflection point

As defined by Grove (1999), at that time President of Intel Corporation, the critical point where the transformation from one business model to another must occur is known as *strategic inflection point* ("*point I*") (Figure 4.1). Obviously, by "*point I*" it doesn't mean a particular point in time but rather a strategic window of time and opportunity during which strategic transformation can take place. This strategic window of time could be months or years (Stockport, 2000). Grove identified a strategic inflection point when the Japanese entered the memory production market and began research and development of new chips to lead the world market. The U.S. companies could not compete against Japanese low-cost, high quality products and some of them were losing the fight and money because they failed to recognize the Japanese business threat. Fortunately, Intel's management recognized the strategic inflection point and adapted the Intel's business from memory chip production to microprocessors one before it was too late. Further examples of the strategic inflection points have occurred in the shipping industry, following the innovation of the containerization that made old international ports, such as New York, unable to compete with those prepared for this innovation, such as Seattle; and in marketing and distribution following the development of e-commerce, as in the case of bookshops like amazon.com compared with Barnes & Noble, or following the establishment of Wal-Mart, probably the largest retailer in the world, in small rural American towns traditionally served only by relatively small stores (Dervitsiotis, 2003; Dervitsiotis, 2004; Grove, 1997).

The strategic inflection point can be depicted on the S-curve. In fact, the growth of a chosen performance parameter, $P(t)$, of a company can be conformed to an S-curve pattern as a function of time, t, which starts when a new business model is adopted (Dervitsiotis, 2003; Dervitsiotis, 2004; Dervitsiotis, 2005; Grove, 1999; Stockport, 2000). In this context, the saturation value of the performance level is the *Business Excellence* (BE). Moreover, the curve's shape makes it easy to see that the company productivity begins to decrease just after the strategic inflection point ("*point I*"), that is the point on the curve where the arc changes from concave to convex (Asthana, 1995; Grove, 1999; Kumar & Kumar, 1992). Therefore, the strategic inflection point ("*point I*") marks the end of a previously successful mindset and of strategies that are no longer effective (Figure 4.1).

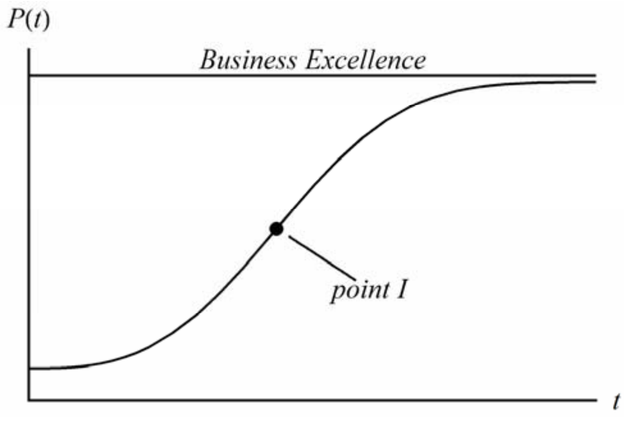


Figure 4.1. The strategic inflection point

At that point, management should begin a strategic transformation because further efforts in the old business model will result in diminishing returns (Asthana, 1995; Dervitsiotis, 2003; Dervitsiotis, 2004; Dervitsiotis, 2005; Stockport, 2000). It was found useful to break this change process into two phases. The first half is the phase in which it is best to *let chaos reign* because management do not know enough to take charge. After that this experimentation phase (the so-called *edge of chaos*) is over, it is time to *rein in chaos*. In fact, the second phase is the moment to take charge again and to be completely explicit in stating the direction of the new business (Grove, 1997). Therefore, a key management task is to monitor the position of the company on its S-curve and prepare itself for jumping at the "*point A*" from the present curve to a new performance curve, based on a new business model that is more suitable for the emerging conditions (Figure 4.2). In fact, upward movement along an S-curve is generally accepted to depict an incremental innovation in the chosen performance parameter, while a transition to a different business model (that has a higher saturation value of the performance level) is graphically depicted as a discontinuous innovation (Corti, 2002; Erto, 1997a; Erto & Lanzotti, 1995; McGrath, 1998). So, we don't have a single S-curve, but we have a series of successive S-curves (D'Avino & Erto, 2007a; Sood & Tellis, 2005).

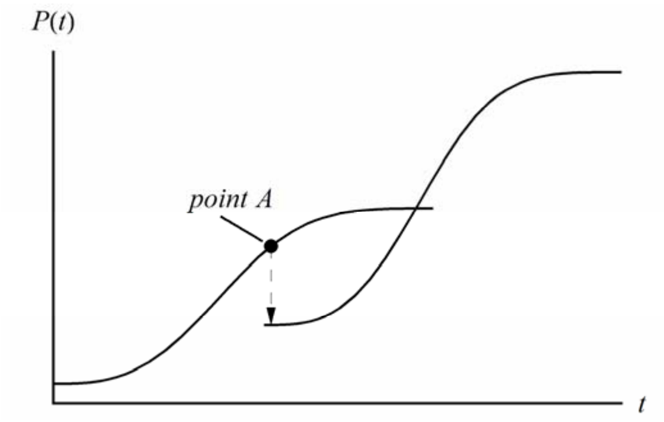


Figure 4.2. Jumping the curve

In this way, the organization can strategically transform itself before it starts to wither (the decline phase is not included in our analysis). In fact, "jumping the curve" must always be made while the company has the ability and "slack" to transform itself. At "*point A*" there is still a momentum from continuing good results of past successful products and markets, which provides the “slack” of required resources to make an effective transition. On the contrary, if the leadership of a successful company isn’t prompt to recognize a strategic inflection point and reacts too late, the needed internal transformation may be too difficult or impossible to make, and decline follows. Moreover, when there is a delayed attempt to jump the curve, the costs may become too high (Dervitsiotis, 2003; Dervitsiotis, 2004; Dervitsiotis, 2005; Stockport, 2000).

Finally, the strategic inflection point can mean an opportunity to rise to new heights, but it may just as likely signal the beginning of the end (Grove, 1999). To survive and maintain a competitive advantage, management should act and re-position the company when the going is at its best. Unfortunately, almost nobody does that: they wait until the signs of a strategic inflection point are incontrovertible, but they only become incontrovertible after the decline has gone so far that nobody can question it. They want the proof that the strategic inflection point has been past (Grove, 1997). Therefore, being helped to understand when time has come to start a long strategic transformation without any hesitation can be a significative survival factor. In this framework, we propose a diagnostic tool in order to support management in this difficult decision-making process.

4.4. A piecewise regression model

It is standard practice to approximate a regression curve by a single model over the entire range of time, which is relevant to the problem. However, for our purposes, we found approximating the regression curve by a sequence of sub-models (*piecewise regression model*) more effective and flexible (D’Avino & Erto, 2007b). Obviously, each sub-model must be joined to the next one at the end of its definition range. It is relatively simple to fit such a model if where the join points are is known in advance. On the contrary, our problem deals with the more difficult case where the join points themselves have to be estimated from the data.

Therefore, we propose the following new piecewise regression model, of the performance level $P(t)$, which is tractable and very adaptive having four *shape* parameters (a_1, a_2, a_3, a_4), two *time* parameters (τ_1, τ_2) and four given constants (P_0, $P_{\lim}$, τ_0, τ_3) for only one explanatory variable, t:

$$\begin{cases} P_1(t) = P_0 + a_1(t-\tau_0)^2 & a_1 > 0, P_0 > 0 \quad \textit{for} \quad \tau_0 \le t \le \tau_1 \\ P_2(t) = a_2 t + a_3 & a_2 > 0 \quad \textit{for} \quad \tau_1 \le t \le \tau_2 \\ P_3(t) = P_{\lim} - \dfrac{a_4}{t} & a_4 > 0 \quad \textit{for} \quad \tau_2 \le t \le \tau_3 \end{cases} \tag{4.1}$$

It is straightforward to show that:

$$\lim_{t\to\tau_0} P_1(t) = P_0 \qquad \lim_{t\to+\infty} P_3(t) = P_{\lim} \tag{4.2}$$

The good applicability of this model is also due a reduction (from six to four) of the number of parameters to be estimated, as shown in the next paragraph.

The model is composed of three sub-models: a branch of parabola, $P_1(t)$, that approximates the birth phase of the new business model; a straight line, $P_2(t)$, that approximates its growth phase, and a branch of translated equilateral hyperbola, $P_3(t)$, that approximates its maturity phase (Figure 4.3). The mathematical formulations of the first and the third sub-models were chosen because their patterns fit well respectively the initial phase of slow growth and the final phase of slow decrease. In particular, the slow pattern of the branch of translated equilateral hyperbola allows to represent the "slack" that company has still at the "*point A*", to transform itself. Moreover, the choice of the three above sub-models is validated by the empirical analysis of our datasets.

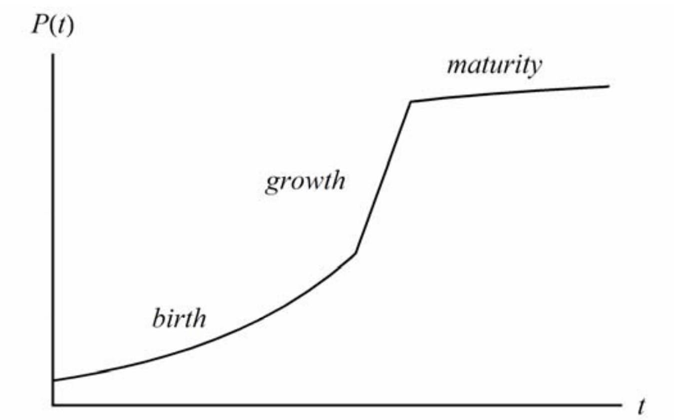


Figure 4.3. The three phases of the business model life cycle

The used notation is:

τ_0 is the initial time (given constant);

P_0 is the initial performance level (given constant);

$P_{\lim}$ is the saturation value of the performance level or the Business Excellence (BE) reachable through the adopted business model (given constant);

τ_1 is the join point between the branch of parabola and the straight line, or the time when the second phase starts (to be estimated);

τ_2 is the join point between the straight line and the branch of translated equilateral hyperbola, or the time when the third phase starts (to be estimated);

τ_3 is the last sampled time (given constant).

For our purposes, the most important parameter is τ_2, since it represents the best point and time to jump to a new performance curve ("*point A*").

4.5. Least squares estimators for piecewise regression

The method of least squares (LS) is used throughout this paper. The number of the parameters to be estimated is six: two time parameters (τ_1 and τ_2) and four shape parameters ($\{a_i\}_{i=1,\dots,4}$). However having the model to be continuous at each join point, the following constraints stand:

$$\begin{cases} P_1(\tau_1) = P_2(\tau_1) \\ P_2(\tau_2) = P_3(\tau_2) \end{cases} \quad \Rightarrow \quad \begin{cases} P_0 + a_1(\tau_1 - \tau_0)^2 = a_2\tau_1 + a_3 \\ a_2\tau_2 + a_3 = P_{\lim} - \dfrac{a_4}{\tau_2} \end{cases} \tag{4.3}$$

Therefore, the number of independent parameters to be estimated is reduced to four. No restriction is placed on the slopes of the adjacent curves.

In order to estimate the unknown parameters, we have to minimize the following residual sum of squares (RSS):

$$RSS(a_i, \tau_j, S, V) = \sum_{k=1}^{S}\left(P_k - P_1(t_k; a_1)\right)^2 + \sum_{k=S+1}^{V}\left(P_k - P_2(t_k; a_2, a_3)\right)^2 + \\ + \sum_{k=V+1}^{T_3}\left(P_k - P_3(t_k; a_4)\right)^2 \tag{4.4}$$

with $V \geq S+1$; $i = 1, \ldots, 4$; $j = 1, 2$; $k = 1, \ldots, n$ (n is the sample size) and P_k being the performance level corresponding to time t_k. The function (4.4) is subject to the following constraints in addition to the constraints (4.3) among parameters:

$$t_S \leq \tau_1 \leq t_{S+1} \qquad t_V \leq \tau_2 \leq t_{V+1} \tag{4.5}$$

where S and V are integer numbers which identify the starting points of the two intervals in which τ_1 and τ_2 must be estimated respectively.

For the complexity of the function (4.4), the solution requires an iterative technique. Following the procedure recommended in Hudson (1966) we searched for the solutions for each likely value of S and V and, then, we chose the estimated values of τ_1 and τ_2 for which RSS reaches its global minimum.

4.6. Application perspective

During the improvement and/or change process, the main task of the top management is to identify and diagnose timely if the moment when transformation must occur has come. In practice, this time can be identified only some time late it has been past since the environmental changes are unpredictable: the management must make any effort to short this time interval. In this context, the above diagnostic tool can provide the proof, which management needs, to overcome the resistance to change. In fact, it shows that the maturity phase has started and, thus, the transformation to the new business model is needed for survival.

In order to highlight the diagnostic power of our model, the piston aircraft engine and jet aircraft engine datasets were analyzed (see Chapter 1). Obviously, the analysis is carried out at the industry-level, since it aims to detect a critical environmental change.

4.6.1 Technological discontinuities in aircraft history

First, we analyzed the piston aircraft engine dataset. In order to minimize the function RSS (4.4), we searched solutions for

$S = 1,\ldots,15 \;\; (t_1 \le \tau_1 \le t_{16})$ and $V = 2,\ldots,16 \;\; (t_2 \le \tau_2 \le t_{17})$ with $V \ge S + 1$

being $n = 17$ the sample size. The convergence of the proposed iterative technique is achieved for each above suitable combination of the values S and V. In this way, the critical values $\hat{\tau}_1$ and $\hat{\tau}_2$ for which RSS is minimized, were obtained without computational difficulties (Figure 4.4):

$\hat{\tau}_1 = 40 = t_{14}$ and $\hat{\tau}_2 = 42.05\,(t_{15} < \hat{\tau}_2 < t_{16})$.

It's interesting to note that, from the adopted t scale, $\hat{\tau}_2 = 42.05$ corresponds to the year 1943. In fact, in the year 1944, after an era of vast experimentation, mass production of jet engine (based on the axial-flow compressor design) as a power plant for the world's first jet-fighter aircraft, the Messerschmitt Me 262, started. It will be remembered as the first use of jet engines in service. Then, following the end of World War II, the jet engines were extensively studied by the victorious allies. Nonetheless, the legacy of the axial-flow engine is seen in the fact that practically all jet engines on fixed wing aircraft have had some inspiration from this design. By the 1950s the jet engine was almost universal in combat aircraft and by the 1960s all large civilian aircraft were also jet powered, leaving the piston engine in niche roles.

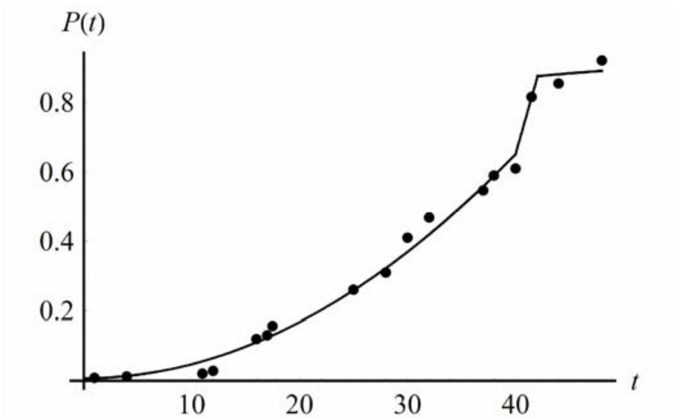


Figure 4.4. The estimated model for piston aircraft engine (normalized) data

Subsequently, we analyzed the jet aircraft engine dataset. In order to minimize the function (4.4), we searched solutions for

$(t_1 \le \tau_1 \le t_{13})$ and $V = 2,\ldots,13$ $(t_2 \le \tau_2 \le t_{14})$ with $V \ge S+1$

being $n = 14$ the sample size. The convergence of the proposed iterative technique is achieved for each above suitable combination of the values S and V. In this way, the critical values $\hat{\tau}_1$ and $\hat{\tau}_2$ for which RSS is minimized, were obtained without computational difficulties as in the previous case (Figure 4.5):

$\hat{\tau}_1 = 24 = t_8$ and $\hat{\tau}_2 = 28.35\,(t_{10} < \hat{\tau}_2 < t_{11})$.

It's interesting to note that, from the adopted t scale, $\hat{\tau}_2 = 28.35$ corresponds to the year 1969. In fact, in the year 1970, the first commercial wide-body aircraft, the Boeing 747, debuted. The Boeing 747 was born from the increase in air travel in the 1960s. The era of commercial jet transportation, led by the enormous popularity of the Boeing 707 and Douglas DC-8, had revolutionized long distance travel. Engineers were faced with many challenges as airlines wanted more seats, more range and lower operating cost. Therefore, the wide-body aircraft is a larger airliner with twin aisles inside the cabin and can accommodate between 200 and 600 passengers. The Boeing 747 was expected to become obsolete after sales of 400 units due to development of supersonic commercial aircraft, but it has outlived the expectations and its production passed the 1000 mark in 1993. The latest development of the aircraft, the 747-8, is planned to enter service in 2009.

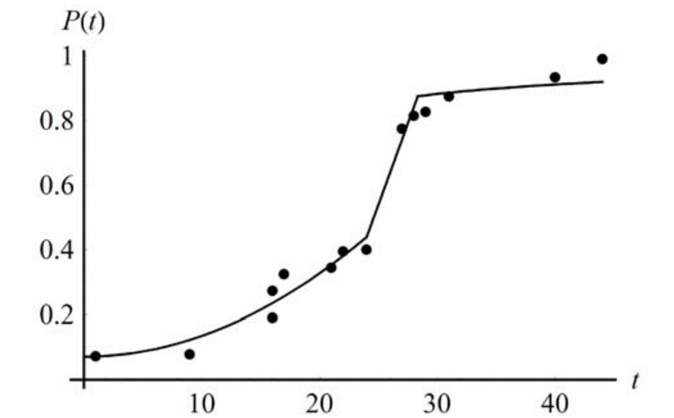


Figure 4.5. The estimated model for jet aircraft engine (normalized) data

4.7. Statistical properties of the proposed method

Before applying a method in practice, knowledge of its statistical properties is crucial. In this work, the results from a simulation study are used to evaluate some measures of performance proposed in the literature (Andersson, 2002; Sonesson, 2003). Data were generated using a set of predetermined values of the parameters of the model (4.1). An error term, ε (that is a random variable generated to be stochastically independent and identically normally distributed with zero mean and constant variance σ^2), was added to each sub-model. The "true" values of the parameters and of the error variance σ^2 were taken to be the quantities obtained from the LS fit to the original jet aircraft engine dataset for each sub-model (Ratkowsky, 1983). In particular, the assumed "true" values of τ_1 and τ_2 were respectively $\tau_1 = 24$ and $\tau_2 = 28.35$. By this means, 1000 sets of simulated data were produced, each of which provided a set of the parameter LS estimates (Ratkowsky, 1983). Consecutively, the histograms of the results for $\hat{\tau}_1$ and $\hat{\tau}_2$ are reported in Figure 4.6.

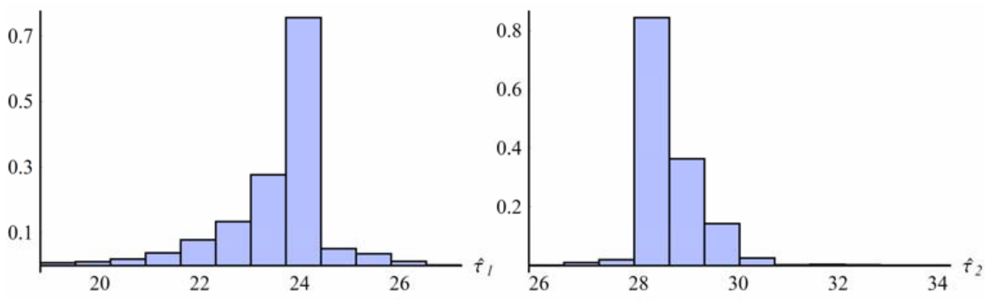


Figure 4.6. Histograms of the results for $\hat{\tau}_1$ and $\hat{\tau}_2$

The Table 4.1 summarizes the properties of the proposed method.

Table 4.1 The measures of performance of the proposed method

Criteria	$\hat{\tau}_1$	$\hat{\tau}_2$
%bias	-1.9	0.77
CED	0.16 (about 2 months)	0.60 (about 7 months)
CEA	0.60 (about 7 months)	0.28 (about 3 months)
PSD	0.61	0.68
***CI* (95%)**	$\{20.74, 25.35\}$	$\{28, 30.06\}$

The used notation is:

$\%bias = \dfrac{\dfrac{\sum_{j=1}^{1000} \hat{\tau}_{i,j}}{1000} - \tau_i}{\tau_i}$ is the bias expressed as a percentage of the true value of the parameters (where $\hat{\tau}_{i,j}$ are the single values of the LS estimates of τ_i for $i = 1, 2$ and $j = 1, \ldots, 1000$);

$CED = E\left\{\hat{\tau}_i - \tau_i \middle| \hat{\tau}_i \geq \tau_i\right\}$ is the conditional expected value of the difference between the estimated values greater than τ_i and τ_i (conditional expected delay time). In this context, we considered only the values of difference greater than 0.1 (about 1 month);

$CEA = E\left\{\tau_i - \hat{\tau}_i \middle| \hat{\tau}_i \leq \tau_i\right\}$ is the conditional expected value of the difference between the estimated values smaller than τ_i and τ_i (conditional expected advance time). In this context, we considered only the values of difference smaller than 0.1 (about 1 month);

$PSD = P(|\hat{\tau}_i - \tau_i| \leq d)$ is the probability of successful detection. It measures the probability that the change point is detected with a delay or advance time no longer than d. In our context, $d = 0.5$ (six months) was considered an acceptable time.

$CI\,(95\%)$ is the 95% confidence interval constructed by percentile method. In fact, from Figure 4.6 and from the results of the hypothesis tests about the coefficients of skewness and kurtosis, it is clear that the parameter estimates $\hat{\tau}_1$ and $\hat{\tau}_2$ are not normally distributed. Therefore, classical confidence intervals are not applicable.

The Table 4.1 shows that the join point LS estimators underestimate τ_1, while they overestimate τ_2. In fact, the *%bias* value is negative for $\hat{\tau}_1$ and positive for $\hat{\tau}_2$. Then, for $\hat{\tau}_1$ the *CEA* is greater than the *CED*, while for $\hat{\tau}_2$ the *CED* is greater than the *CEA*. However, these values are considered acceptable in this context. Moreover, the *PSD* value is greater than 50%. Finally, the $CI\,(95\%)$ for $\hat{\tau}_2$ is smaller than one for $\hat{\tau}_1$. Therefore, the estimate accuracy for $\hat{\tau}_2$ is greater than one for $\hat{\tau}_1$.

Another important analysis consists in verifying how many data, after that the "*point A*" has been past, the procedure is able to estimate the join points and how robust are their estimates. To this end, we estimated the parameters after having ignored the last m data with $m = 0,1,2,3$ since $t_{10} < 28.35 < t_{11}$. The obtained values are presented in Table 4.2, where n is the new simulated sample size and $\hat{\tau}_1$ and $\hat{\tau}_2$ are the new corresponding estimates of the join points.

Table 4.2 $\hat{\tau}_1$ *and* $\hat{\tau}_2$ *with* $m = 0,1,2,3$

m	n	$\hat{\tau}_1$	$\hat{\tau}_2$
0	14	$24 = t_8$	$t_{10} < 28.35 < t_{11}$
1	13	$24 = t_8$	$t_9 < 27.57 < t_{10}$
2	12	$24 = t_8$	$t_9 < 27.46 < t_{10}$
3	11	$24 = t_8$	$t_9 < 27.34 < t_{10}$

The procedure appears robust since $\hat{\tau}_1$ is always equal to 24 and $\hat{\tau}_2$ is included between t_9 and t_{11} for each value of m. Consequently, in this case we would have been prompt to obtain a suitable estimate of the join points immediately after that the “true” value of the “*point A*” has been past. In the Figure 4.7, the estimated model with $m = 3$ is presented. Obviously, $\hat{\tau}_2$ is anticipated owing the missing data. On the other hand, this negative bias gives a precautionary alarm.

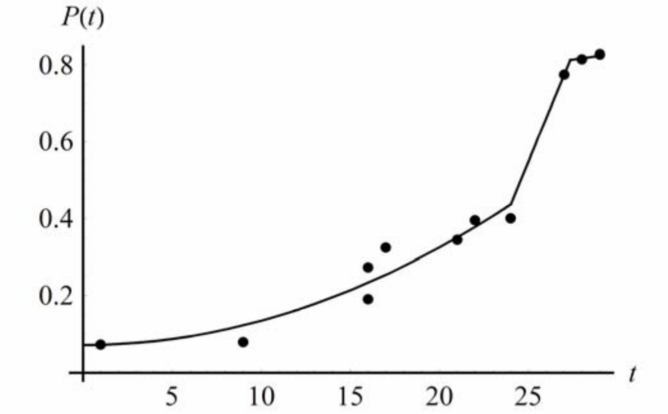


Figure 4.7. The estimated model for jet aircraft engine (normalized) data with $m = 3$

4.8. Conclusions

In current environment of faster and faster changes, time-based strategy is becoming an important weapon to achieve competitive advantage and survival. The literature about change process is very extensive, but the greater part of the works concerning this topic considers case studies and highlights the important factors that affect a successful transformation. Differently from them, this paper deals with a specific operative aspect of the problem by providing the managers with an effective statistical methodology to face the most important task: diagnosing if the time to jump the curve has been past. In this way, management will become aware timely of a critical environmental change that may pose a threat to the company’s future success. In fact, the applicative example concerning the technological discontinuities in aircraft history shows the diagnostic power of the model. Finally, the statistical properties of the method were evaluated.

Conclusions

In our era of increasingly rapid technological, social and economic changes, the product and/or process innovation should be planned and managed as well as any other productive activity. In particular, leader companies should develop organizational plans that encourage the external environment monitoring, self-assessment and constant renewal. In this way, they can face up to the unexpected circumstances that are almost certain to arise. On the other hand, each change process requires some difficult steps and, thus, gives rise to resistance to change, especially in successful companies. In fact, the change requires to shift resources away from these areas where the company currently enjoys success to an area that is new and unproven. Therefore, in western economies the average corporate life is about 40 years and numerous corporate failures occur when environmental conditions change dramatically. Moreover, the failure rate of an innovative idea is very high (90-94 out of 100 proposals of innovation undergo substantial failure in the EU and in the USA). Low reliability in the long run and sensitivity to the usage conditions are the factors that determine the failure of innovation. In this context, the transfer of time-based statistical methodologies to companies can be a significative survival factor. In this way, they will be helped to understand when time has come to start a strategic transformation and to overcome the usual breakout friction in order to substitute the previously successful strategic formulas. Moreover, the development of specific statistical methods aimed to monitor innovation quality and motivate innovation investments, is mandatory. Obviously, the problems of managing innovation are so varied and complex that multiple bodies of knowledge are likely to be required. However, the statistical methodologies help to make sense of what previously appeared to have been random or contradictory phenomena. Therefore, some original diagnostic tools have been proposed in this work. They can constitute a useful starting point for analyzing and explaining the potential paradigms emerging in the study of innovation process.

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