

Statistical Applications to Thermal Analysis

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1. Application of nonparametric regression methods

1.1. Introduction

An important topic in thermal analysis is the statistical analysis. There are several works in the thermal analysis literature that use regression models to account for the relationship between the variables of interest in this field. Many of them are based on the Arrhenius equation modified by Sestak and Berggren [27] and were discussed by Vyazovkin [29] and compared by many authors [3].

The response variable is often heat flow or sample mass along the experiment, while typical explanatory variables are temperature or time. Some important properties of the materials can be directly measured or easily calculated from the response variables. They include characteristic temperatures of different processes, i. e. melting and glass transition temperatures, thermal stability, specific heat at different temperatures, enthalpy associated to chemical reactions and physical changes. In addition, kinetic analysis of the processes can be performed from the thermal analysis data. The study of these data gives useful insight for materials characterization.

It is relevant to point out that the estimation of the first two derivatives is also an important issue. In the case of weight loss processes, the TGA first derivative (DTG) can be compared to the DSC trace. The DTG trace is sharper and more accurate to detect the onset and end points of the processes. It is especially interesting when studying overlapped processes. This higher quality of DTG compared to DSC comes from two differences between the both techniques:

1. The TGA response is almost instantaneous and immediately reflects the weight changes, while the DSC signal is affected by a thermal lag (the heat from the sample takes some time to travel through the crucible to the detector).
2. The heat diffusion in the crucible smoothes the signal before reaching the detector.

TGA and DSC, therefore, give direct mass and calorimetric measurements for whose a good estimation accuracy is desired.

The main aim of this work is to accurately estimate the functional relationship between an explanatory variable X , typically time or temperature, and a response variable Y , often weight (for TGA curves) or heat flow (for DSC curves). The following nonparametric regression model is assumed to hold:

$$Y_i = m(X_i) + \varepsilon_i, \quad i = 1, 2, \dots, n. \quad \text{with } E(\varepsilon_i) = 0. \quad (1)$$

where m is the regression function of Y given X and ε_i is a term accounting for the measurement error (for instance that of the calorimeter). Throughout the paper it will be assumed that the design is fixed (most of the time the X_i are equally spaced in practice), and the error is homoscedastic, i. e., $Var(\varepsilon_i) = \sigma^2$ for $i=1,2,\dots,n$.

The methods used in practice to smooth DSC or TGA curves by means of nonparametric weights do not incorporate any automatic optimal smoothing parameter selection. In some cases they are even based in moving average procedures, going back to the early work by Savitzky and Golay [25]. For this reason the bad fitting is very evident in many cases, specially in the first and second derivative estimation.

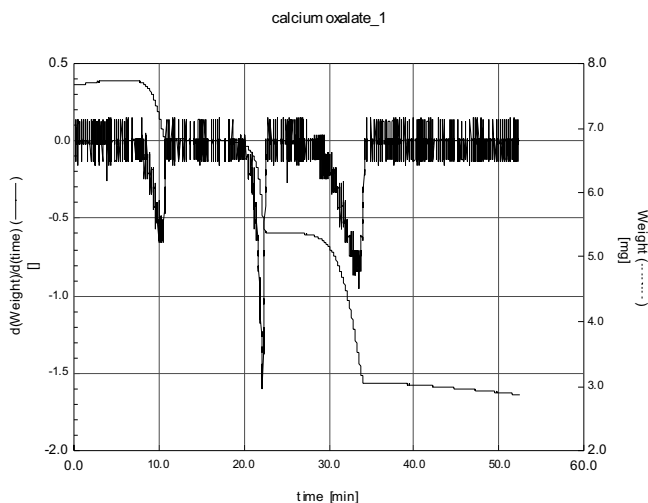


Figure 1. TGA curve for the calcium oxalate sample (dashed line) and first derivative (solid line) using the RSI Orchestrator

Figure 1 shows a fit of a TGA curve of calcium oxalate and its first derivative using one of the standard computer packages in this field, the Orchestrator® by Rheometric Scientific Incorporation®. The smoothing software incorporated to this package enables selection of the amount of smoothing "by hand" but not any automatic estimated optimal smoothing parameter that takes into account the non negligible error dependence. The aim of this paper is precisely to provide an automatic selection of the amount of smoothing to be used in these contexts.

1.2. Technical background

Nonparametric regression methods will be used to estimate the function m without specifying any a priori parametric model. The key idea is to assume that m is a smooth function and approximate $m(x)$ by averaging the Y -observations in a neighbourhood of x :

$$m(x) = \frac{1}{n} \sum_{i=1}^n W_{ni}(x) Y_i, \text{ with } \sum_{i=1}^n W_{ni}(x) = 1. \quad (2)$$

where $W_{ni}(x)$ is the weight that the i -th observation gives to the point x . Typically these weights depend on some smoothing parameter h and some kernel function K . The choice of the smoothing parameter is crucial since it controls the amount of smoothing used in the estimation. Among the great deal of nonparametric estimators for m we

mention the Nadaraya-Watson estimator (see [18]), Priestley-Chao estimator (see [21]), Gasser-Müller estimator (see [16]) and the local polynomial estimator (see [9]).

Since our aim is to estimate the regression function as well as its first two derivatives it is very natural to use local polynomial estimators, which additionally have good properties for estimating at the boundary.

1.3. Local polynomial estimator

The local polynomial estimator was introduced by Stone [28] and Cleveland [5] but it has not been extensively used until the nineties, after publication of the papers by Ruppert and Wand [23] and Fan and Gijbels [9].

The idea behind the local polynomial regression estimator is to use weighted least squares to perform a local fit to a polynomial of degree specified in advance. More precisely the regression function ($j=0$) and its derivatives ($j=1,2,\dots,p$) at a given point x are estimated by

$$\hat{m}^{(j)}(x) = j! \beta_j(x) \quad j = 0, 1, 2, \dots, p, \tag{3}$$

where

$$\beta = (\beta_0, \beta_1, \dots, \beta_p) = \arg \min_{\beta} (Y - X\beta)' W (Y - X\beta) \tag{4}$$

$$X = \begin{pmatrix} 1 & (X_1 - x) & \dots & (X_1 - x)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (X_n - x) & \dots & (X_n - x)^p \end{pmatrix}, Y = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}$$

and $W = \text{diag}\{K_h(x_i - x)\}$ is the $n \times n$ matrix that contains the weights that every datum in the sample gives to the point of interest. An explicit expression for the vector β is:

$$\beta = (X'WX)^{-1} X'WY. \tag{5}$$

1.3.1. Practical choice of the kernel and the order of the local polynomial

In order to use the local polynomial estimator we need to choose the kernel function, K , the degree of the polynomial, p , and the bandwidth, h . The choice of K and p is of secondary importance with respect to the smoothing parameter h . Fan and Gijbels [10] recommend using the Epanechnikov kernel, since it minimizes the asymptotic mean squared error for an optimal bandwidth. They also suggest to choose p as any integer larger than the order of derivative of interest, j , such that $p-j$ is odd. For instance we could take $p=1$ for estimating the regression function itself, while $p=3$ could be used for estimating the second derivative of the regression function. In general, based on the bias decreasing and variance increasing with p , an advisable practical choice is to set $p-j=1,3$.

Some drawback of the local polynomial estimator is that its conditional variance tends to infinity when the neighbourhood of the interest point (using a compact support kernel) contains no more than $p+3$ data points. This problem, pointed out by Seifert and

Gasser [26], can be solved performing a local increasing of the smoothing parameter whenever it occurs.

For dependent data, as those we are dealing with, the classical local polynomial regression estimator can still be used, although its asymptotic mean squared error depends now on the sum of covariances of the error process. An alternative approach has been proposed by Francisco and Vilar-Fernández [13], by using generalized least squares ideas to account for the dependence structure.

1.3.2. Bandwidth selection criteria

Typical bandwidth selection procedures are based on minimizing the empirical version of some criterion that accounts for the error between the nonparametric v -th derivative regression estimation and its underlying counterpart. For instance, using the mean squared error at a given point x :

$$MSE_x(h) = E(\hat{m}_h(x) - m(x))^2, \tag{6}$$

we obtain local optimal bandwidths. Global criteria, as the MISE, can be obtained by considering global distances between the estimator and the true curve. Most of the times these measures can be written as integrated versions of the some local criterion (Eq. 6). For instance the mean integrated squared error can be written as:

$$MISE_x(h) = E \int (\hat{m}_h(x) - m(x))^2 w(x) dx, \tag{7}$$

for some weight function w . This measure can be easily decomposed as a sum of the integrated variance and the integrated squared bias.

Under independence in the error structure and assuming that $v+p$ is odd, Fan and Gijbels [10] give asymptotic expressions for the bias and the variance of the local polynomial estimator:

$$\begin{aligned} Bias(m^v(x)) &= h_n^{p+1-v} \frac{m^{p+1}(x)}{(p+1)!} v! B_v (1 + o(1)), v = 0, 1, \dots, p, \\ Var(m^v(x)) &= \frac{1}{nh_n^{2v+1}} \frac{c(\mathcal{E})}{f(x)} (v!)^2 V_v (1 + o(1)), v = 0, 1, \dots, p, \end{aligned} \tag{8}$$

where, in (8), f is the design density and the values B_v and V_v depend on the kernel function (see Ruppert, Sheather and Wand [24] for details). Using the smoothing parameter minimizing the asymptotic expression of MISE can be easily found to be:

$$h_{AMISE} = C_{v,p}(K) \left(\frac{\sigma^2}{n \int (m^{p+1}(x))^2 w(x) f(x) dx} \right)^{\frac{1}{2p+3}} \tag{9}$$

where the constants $C_{v,p}(K)$ can be computed as follows:

$$C_{v,p}(K) = \left[\frac{(p+1)!^2 (2v+1) \int K_v^{*2}(t) dt}{2(p+1-v) \left\{ \int t^{p+1} K_v^*(t) dt \right\}^2} \right]^{\frac{1}{2p+3}}$$

with $K_v^*(t) = \left(\sum_{l=0}^p S^{vl} t^l \right) K(t)$, S^{vl} are the elements of the matrix S^{-1} and $S = (\mu_{j+l})_{j,l=0}^p$ with $\mu_j = \int u^j K(u) du$.

In the dependent error case similar formulas can be obtained based on parallel expressions to bias and varianza (Eq. 8). For the asymptotic mean integrated squared error (see Francisco and Vilar-Fernández [13] for details) the following expression gives some approximation of a reasonable criterion to select h . Therefore, an asymptotically optimal bandwidth (in the sense of AMSE) to estimate the v -th derivative of the regression function is:

$$h_{opt,L} = C_{v,p}(K) \left(\frac{c(\mathcal{E})}{n(m^{p+1}(x))^2 w(x) f(x)} \right)^{\frac{1}{2p+3}}$$

$$h_{opt,G} = C_{v,p}(K) \left(\frac{c(\mathcal{E})}{n \int (m^{p+1}(x))^2 w(x) f(x) dx} \right)^{\frac{1}{2p+3}} \tag{10}$$

where $c(\mathcal{E}) = \sum c(k)$ and $c(k)$ is the lag k autocovariance of the errors \mathcal{E}_i .

The previous formulas are valid if $v+p$ is odd. If $v+p$ is even the expressions for the optimal bandwidths are

$$h_{opt,L} = C_{v,p}(K) \left(\frac{c(\mathcal{E})}{n(m^{p+2}(x))^2 w(x) f(x)} \right)^{\frac{1}{2p+5}}$$

$$h_{opt,G} = C_{v,p}(K) \left(\frac{c(\mathcal{E})}{n \int (m^{p+2}(x))^2 w(x) f(x) dx} \right)^{\frac{1}{2p+5}} \tag{11}$$

1.3.3. Two-stage plug-in bandwidth selector

Some of the most popular procedures for bandwidth selection in nonparametric curve estimation are the plug-in methods. These methods estimate the minimizer of either the AMSE or AMISE. For the local polynomial estimator under dependence, the plug-in local and global bandwidth selectors are some estimators of expressions (Eq. 10 and 11). Therefore some estimators of $c(\mathcal{E})$, the sum of autocovariances, and the $(p+1)$ -th derivative of the regression function are needed.

Estimating the autocovariances sum

Although $c(\mathcal{E})$ can be estimated through the spectral density of the \mathcal{E}_i our approach will be somewhat simpler. Let us assume that the \mathcal{E}_i follow an autoregressive

process of order 1 (AR(1)) with first order autocorrelation ρ . Then $c(\varepsilon)$ can be written in terms of the error variance and the autocorrelation coefficient:

$$c(\varepsilon) = \sum_{k=-\infty}^{\infty} c(k) = \sum_{k=-\infty}^{\infty} \sigma^2 \rho(k) = \sigma^2 \frac{1+\rho}{1-\rho} \tag{12}$$

We now compute the residuals: $\varepsilon_i = Y_i - \hat{m}_h(x_i)$, using some preliminary smoothing parameter h , and then find an estimator for the variance $\sigma^2 = \frac{1}{n} \sum_{i=1}^n (\hat{\varepsilon}_i - \bar{\varepsilon})^2$,

with $\bar{\varepsilon} = \frac{1}{n} \sum_{i=1}^n \hat{\varepsilon}_i$ and an estimator of the first lag autocorrelation coefficient:

$$\hat{\rho} = \frac{\sum_{i=1}^{n-1} (\hat{\varepsilon}_i - \bar{\varepsilon})(\hat{\varepsilon}_{i+1} - \bar{\varepsilon})}{\sum_{i=1}^n (\hat{\varepsilon}_i - \bar{\varepsilon})^2} \tag{13}$$

Then

$$c(\varepsilon) = \sigma^2 \frac{1+\hat{\rho}}{1-\hat{\rho}}.$$

Pilot bandwidths choice

The plug-in method requires to estimate the unknown quantities in (Eq. 10 and 11) and by some values $h_{PI,L}$ and $h_{PI,G}$. For a fixed integer, v , the method is used to estimate $m^{(v)}$ using local polynomials of degree p . Estimation of $c(\varepsilon)$, already considered in the previous subsection, requires the choice of a preliminary bandwidth h_1 , needed to compute the residuals.

Plug-in bandwidth selectors also need to estimate the $(p+1)$ -th derivative of the regression function, m . This may be done, once more, by means of local polynomial fitting for estimating the v derivative ($v=p+1$) using local polynomials of degree $p+2$. This requires the choice of a preliminary pilot bandwidth, $h_2^{(1)}$. To determine some automatic method for selecting $h_2^{(1)}$ we face similar problems when looking at the expression for the optimal (local or global) smoothing parameter in this context. More specifically, there are two unknown terms to be estimated: $c(\varepsilon)$ already considered above, and the $(p+1)$ -th derivative of m . The idea behind the two-stage plug-in method is to propose some prepilot bandwidth, $h_2^{(0)}$, by looking at the expression for the asymptotically optimal bandwidth for this new problem:

$$h_2^{(0)} = C_2 \delta n^{-\frac{1}{2p+7}} \tag{14}$$

where δ is some estimator of the scale and C_2 is some constant that does not depend on the data. Since in the thermogravimetric experiments the design is equispaced, or nearly

equispaced, we made the choice $\delta = (x_n - x_1)/(n-1)$. The value of C_2 has been adjusted by some heuristic approach to be detailed later.

Parallel problems appear when selecting h_1 . In practice we used a local linear estimator and a single-stage plug-in procedure leading to:

$$h_1 = C_1 \delta n^{-\frac{1}{5}} \tag{15}$$

for some constant C_1 that has been obtained by heuristic arguments.

In order to obtain some practical value for the constants C_1 and C_2 we use a calibration sample of a DSC curve. This sample of $n=950$ equally spaced data corresponds to calcium oxalate monohydrate. Using the initial bandwidth $h_1=6$ to compute the residuals for estimating the autocovariances sum, we have selected several possible values for the prepilot bandwidth $h_2^{(0)}$ for which the final bandwidths of the two-stage plug-in procedure have been computed. The results are collected in Table 1. This table shows how the sensitivity of h_{pl} to the choice of the prepilot bandwidth, $h_2^{(0)}$, is very low. When estimating the regression function, a factor of 10 in the prepilot bandwidth gives a factor of 4 in the pilot bandwidth and finally a factor of 1.5 in the plug-in bandwidth.

For estimating the first and second derivatives, the plug-in bandwidth selector is rather stable with respect to the choice of the prepilot bandwidth, although not so much as for estimating m . Direct inspection of the results obtained (not reported here) show that $h_1=6$ is a reasonable choice. On the other hand, the values $h_2^{(0)}=30$, for m , $h_2^{(0)}=28$, for m' and $h_2^{(0)}=30$, for m'' seem to be reasonable choices for the prepilot bandwidth $h_2^{(0)}$.

Table 1. Pilot and final bandwidths of the two stage global plug-in procedure for estimating m , $v=0,1,2$.

	m	m	m'	m'	m''	m''
$h_2^{(0)}$	$h_2^{(1)}$	$h_{pl,G}$	$h_2^{(1)}$	$h_{pl,G}$	$h_2^{(1)}$	$h_{pl,G}$
	$v = 2, p = 3$	$v = 0, p = 1$	$v = 3, p = 4$	$v = 3, p = 4$	$v = 4, p = 5$	$v = 2, p = 3$
10	6.860839	1.01116	4.56602	2.6356	4.3589	2.7163
20	9.592215	1.07833	7.61298	3.2715	9.0604	4.6653
30	11.928195	1.13428	9.67675	3.5414	11.9025	5.3950
40	14.038808	1.18431	11.5646	3.7621	13.7104	5.7591
50	16.379445	1.23940	12.8962	3.9113	16.0595	6.2005
100	26.760712	1.47904	22.5909	4.9377	28.3775	8.3594

Having these bandwidths in mind Table 2 contains the proposed choices for the pilot bandwidth h_1 and the prepilot bandwidth $h_2^{(0)}$.

Table 2. Values suggested for C_1 , C_2 , h_1 and $h_2^{(0)}$ for estimating m^v .

v	0	1	2
C_1	24	24	24
C_2	64	52	51
h_1	$C_1 \delta n^{-\frac{1}{5}}$	$C_1 \delta n^{-\frac{1}{5}}$	$C_1 \delta n^{-\frac{1}{5}}$
$h_2^{(0)}$	$C_2 \delta n^{-\frac{1}{9}}$	$C_2 \delta n^{-\frac{1}{11}}$	$C_2 \delta n^{-\frac{1}{13}}$

1.3.4. Computational issues

One of the problems that may appear in practice when using the local polynomial estimator is the fact that the matrix $X'WX$ is singular or close to be singular. This occurs very often when the kernel has compact support, the design is equispaced and the bandwidth is small. Let consider a fixed point, x_0 , where the estimation will be performed using a bandwidth h . Assume that the support of the kernel is $[-1,1]$, then only the x_i 's falling in the interval $[x_0-h, x_0+h]$ will be used to obtain the value of the estimator at x_0 . Seifert and Gasser [26] have studied the case $\det(X'WX)=0$ as well as conditions for finite variance of the local polynomial estimator reaching to the following conclusions.

1. Estimation at the point x_0 requires, at least, $p+1$ points in the interval $[x_0-h, x_0+h]$. This condition is more and more restrictive as p increases.

2. In order to warranty that the variance of the estimator is finite, at least $p+3$ data points should fall within the interval $[x_0-h, x_0+h]$.

For both reasons whenever the final two-stage plug-in bandwidth or any auxiliary bandwidth is not large enough such that the interval $[x_0-h, x_0+h]$ contains $p+3$ points, the bandwidth is increased up to a value that meets this condition.

Along this unit, both the plug-in local and global bandwidth selectors have been considered. However, sometimes the global bandwidth may suffer of numerical problems, as those mentioned above, in the boundary of the support. In such cases, the global bandwidth has turned to be a local one in the boundary. In principle, the local plug-in bandwidth seems to be a more accurate smoothing parameter for estimating the regression derivatives in a grid of points. However it is clear that the algorithm becomes computationally much more time consuming.

It is evident that using a single smoothing parameter instead of a different one for every point in a grid makes a difference in terms of computations. However, there are some aspects that make the global bandwidth algorithm even much more efficient for an equispaced design. In that case, the matrix $(X'WX)^{-1}$ does not change when the estimator is evaluated at any design point, x , such that $x_0 < x-h$ and $x+h < x_n$. The reason is that the distances between x and the x_i 's falling within the interval $[x-h, x+h]$ do not change when $x \in (x_1+h, x_n-h)$. This means that the matrix $(X'WX)^{-1}$ used to compute the local polynomial estimator at x_i does not change for $i=\ell, \ell+1, \dots, u-1, u$ where

$l = \lceil h/\delta \rceil + 2$ and $u = n - \lceil h/\delta \rceil - 1$. For those i outside this range the matrix $(X'WX)^{-1}$ has to be explicitly computed at every different point.

In order to save calculations for computing the estimators at the point $x = x_p$, let us write the (i,j) -th element of the matrix $(X'WX)$:

$$(X'WX)_{i,j} = \sum_{r=1}^n (x_r - x_p)^i W_r^{(p)} (x_r - x_p)^j = \sum_{r=1}^n (x_r - x_p)^{i+j} W_r^{(p)} \tag{16}$$

where $W_r^{(p)} = K_h(x_r - x_p)$ is the r -th diagonal element of W . Using the fact that $K(u) = 0 \forall u \in [-1, 1]$ we have that

$$\left| \frac{x_r - x_p}{h} \right| > 1 \Rightarrow W_r^{(p)} = 0$$

or equivalently:

$$W_r^{(p)} \neq 0 \Rightarrow x_r - x_p \in [-h, h] \Leftrightarrow r \in \left[p - \left\lceil \frac{h}{\delta} \right\rceil, p + \left\lceil \frac{h}{\delta} \right\rceil \right]$$

By defining the indices $s_1 = p - \lceil \frac{h}{\delta} \rceil$ and $s_2 = p + \lceil \frac{h}{\delta} \rceil$ we find a faster to evaluate expression for the (i,j) -th element of the matrix $(X'WX)$:

$$\sum_{r=s_1}^{s_2} (x_r - x_p)^{i+j} W_r^{(p)} = \frac{\delta^{i+j}}{h} \sum_{k=-\lceil \frac{h}{\delta} \rceil}^{\lceil \frac{h}{\delta} \rceil} k^{i+j} K\left(\frac{k\delta}{h}\right)$$

It is clear that these implementation reduces the number of calculations for computing the estimator at a given point from $O(n)$ to $O((h/\delta))$. This reduction is specially important for moderate bandwidths. In practice, for many of the thermogravimetric data sets we used, the computer time could be reduced by a factor of 10 to 20.

1.4. Conclusions

In this section we include the results obtained using the local polynomial estimator with two-stage plug-in bandwidth with covariances sum estimated for a sample of calcium oxalate. For comparison purposes we show the results obtained, for the same sample, using one of the smoothing routines incorporated to one of the standard software packages in calorimetry, the RSI Orchestrator.

This adaptive smoothing method was thought for TGA experiments at constant heating rate, but should perform identically well in curves from other thermal analysis experiments where the explanatory variable is time (for cases of constant heating rate or isothermal experiments) or temperature (in the case of constant heating rate).

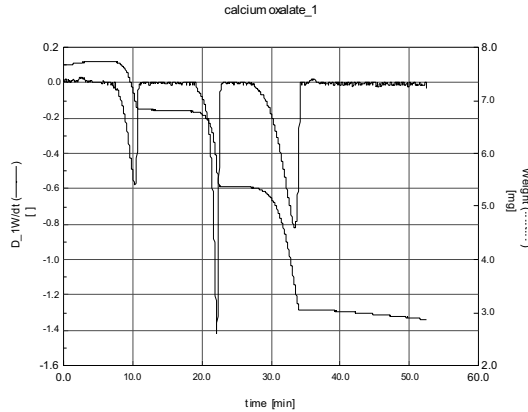


Figure 2. The automatic smoothing obtained using the two-stage global plug-in bandwidth.

2. Kinetic study using the logistic model regression

2.1. Introduction

TG is widely used to determine kinetic parameters for polymer decomposition. Both isothermal and dynamic heating experiments can be used to evaluate kinetic parameters. Each has advantages and disadvantages. In dynamic thermogravimetric analysis (TGA), the mass of the sample is continuously monitored while the sample is subjected, in a controlled atmosphere, to a thermal program, where the temperature is ramped at a constant heating rate. Ideally, a single thermogram has been said to be equivalent to a very large family of comparable isothermal volatilization curves and, as such, constitutes a rich source of kinetic data for volatilization [2].

The classical way to study the kinetics of these processes by TGA starts from the assumption that the weight loss follows the Arrhenius equation:

$$k(T) = A \cdot \exp\left(-\frac{E}{RT}\right) \quad (17)$$

where k , the reaction rate depends on the temperature, T . E , the activation energy may be considered constant in each degradation process (that appears as a clear step in the mass trace) since the degradation mechanism is supposed not to change in a narrow range of temperatures. A is another constant that, in the case that the kinetics follow a reaction order model, may be calculated from $A = m_t^n$, where n is the reaction order.

2.2. Other models

Many other models start from the Arrhenius equation, modified by Sesták-Berggren [3]:

$$\frac{d\alpha}{dt} = k(\alpha)^m (1-\alpha)^n [-\ln(1-\alpha)]^p$$

where n , m and p are constants. Two of the most used derivative models based in that equation are Freeman and Carroll [14], and Friedman [15].

There are also some integrable models, like Ozawa [19], Flynn [8] and the one proposed by Popescu, C. [20], that allows for calculation of n and A from TGA data obtained at several heating rates. The method proposed by Conesa [6] considers that some organic fractions of the sample decompose independently giving an organic residue and an inorganic fraction. This model gave good correlation with the weight loss derivative data for different rubbers [10]. The method proposed by Carrasco F. and Costa J. [3] has been successfully applied to the thermal degradation of polystyrene. Although the application of these models to specific cases has been checked by detailed statistical studies, all of them are based on the Arrhenius equation and can not be generally applied to material degradations following very different kinetics. Moreover, its methodology is sometimes uneasy.

It has been said for methods based on one simple heating rate that quite different reaction models fit the data equally well (from the statistical point of view) whereas the numerical values of the corresponding Arrhenius parameters crucially differ (Vyazovkin [29]). Its physical meaning is obscure and no predictions can be done outside the range of experimental temperature (Vyazovkin). Other authors deemed the Arrhenius model inadequate for the calculation of kinetic parameters from non-isothermal thermogravimetric curves [13]. Moreover, arising from the Kinetics Workshop, held during the 11th International Congress on Thermal Analysis and Calorimetry (ICTAC) in Philadelphia, USA, in 1996, sets of kinetic data were prepared and distributed to volunteer participants for their analysis using any, or several, methods they wished. The results obtained by each researcher were different than the ones obtained by the others, Brown, M. et al. [2]. All of this confirms our believing that the existing models cannot be generally applied and sometimes it is not clear which one is the best suitable to each case. That is the reason to propose an alternative model that will be described in the following sections.

2.3. Logistic model proposed

This model proposes to decompose the TGA trace in several logistic functions, assuming that each of the functions represents the degradation kinetics of each component of the sample. Even in the case of homogeneous materials, it is supposed that several different structures may exist, each one following its specific kinetics that may be different from the others. In this model, it is assumed that a TGA trace may be fitted by a combination of logistic functions:

$$Y(t) = \sum_{i=1}^k w_i f(a_i + b_i t)$$

$$f(t) = \frac{e^t}{1 + e^t} \quad (17)$$

where $i = 1, 2, \dots, k$ represent different components from the weight loss process point of view, not necessarily different chemical compounds.

In order to modelise the weight loss along the time, it is supposed that the candidate functions to estimate the weight along the time ($t, Y_i(t)$) have to verify that when $t \rightarrow \infty$ the response $Y_i(t)$ should tend to 0. It implies that the b_i parameters have to be negative. When $t = 0$, the $Y_i(t)$ function has to tend to the mass of the original

sample and the $Y_i(t)$ functions have to tend to the mass of each component in the original sample, that is, the $w_i(t)$ constants correspond to the weight loss of the sample in each weight loss process. These weight loss processes generally appear as clear steps of the TGA trace.

The function $Y(t)$ that represents the overall TGA trace may be expressed as a sum of $Y_i(t)$ functions like this:

$$Y_i(t) = w_i f(a_i + b_i t)$$

The constants a_i and b_i are calculated taking into account that the b_i values represent the slope of the weight steps while the change of scale comes from the a_i/b_i rates. The w_i values mean the weight of each component in the sample.

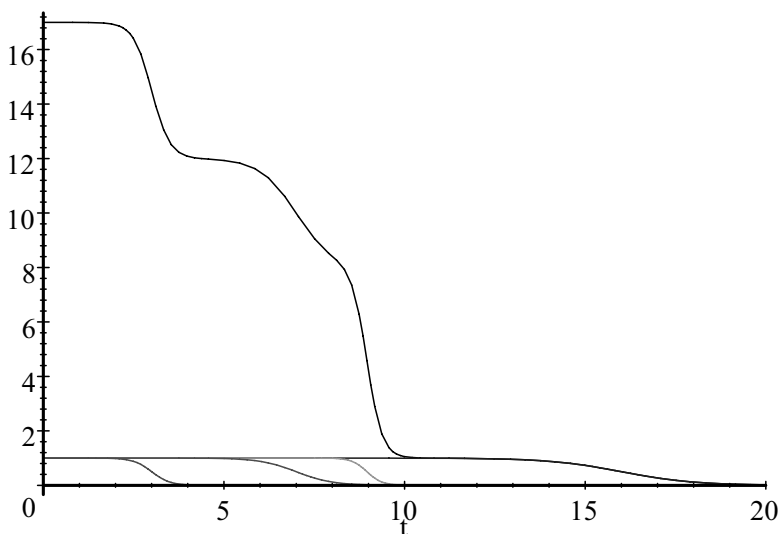


Figure 3. Function obtained from the sum of 4 simple logistic functions.
 $g(t) = 5f(12 - 4t) + 4f(14 - 2t) + 7f(43 - 5t) + f(16 - t)$

2.3.1. Kinetic study using the logistic model

Once the regression function of the TGA trace was obtained, it is immediate to obtain derivatives. Thus, for example, the first derivative of the TGA trace (DTG), which is used by many kinetic models since it represents the weight loss rate along the time, may be expressed by the following equation (18):

$$dTGA(t) = \sum_{i=1}^k w_i b_i f'(a_i + b_i t) \quad (18)$$

$$f'(t) = \frac{e^t}{(1 + e^t)^2}$$

Analyzing, for example, its first component, $i=1$,

$$f(a_1 + b_1 t) = \frac{e^{12-4x}}{1 + e^{12-4x}}$$

Its first derivative is:

$$f'(a_1 + b_1 t) = \frac{-4e^{12-4x}}{(1 + e^{12-4x})^2}$$

Its second derivative results:

$$f''(a_1 + b_1 t) = -16e^{12-4x} \frac{(-1 + e^{12-4x})}{(1 + e^{12-4x})^3}$$

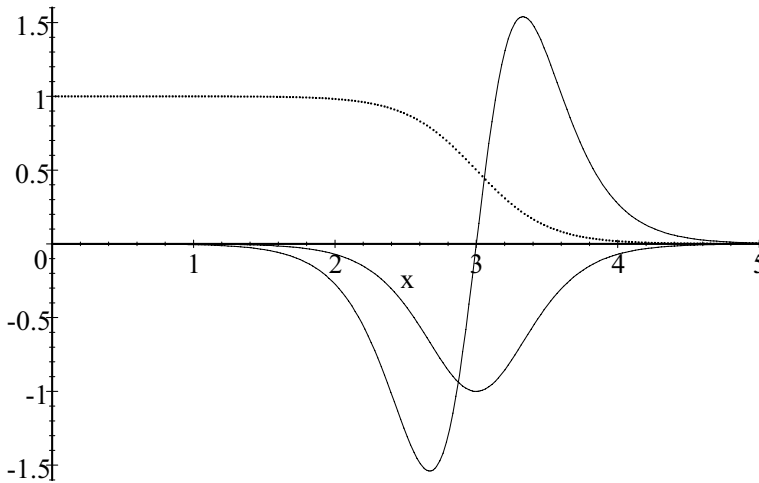


Figure 4. The plots of the f function and its first and second derivatives are shown.

Other possible interpretation of the logistic parameters is obtained applying a change of scale and position. It improves equation (18) since the new values show the weight loss rate b'_i and the exact position in the time axis of the point corresponding to the half weight loss of each step a'_i :

$$Y_i(t) = w_i f\left(\frac{t - a'_i}{b'_i}\right) \tag{19}$$

Anyway it simply consists in a linear transformation of the new parameters that may be obtained indistinctly.

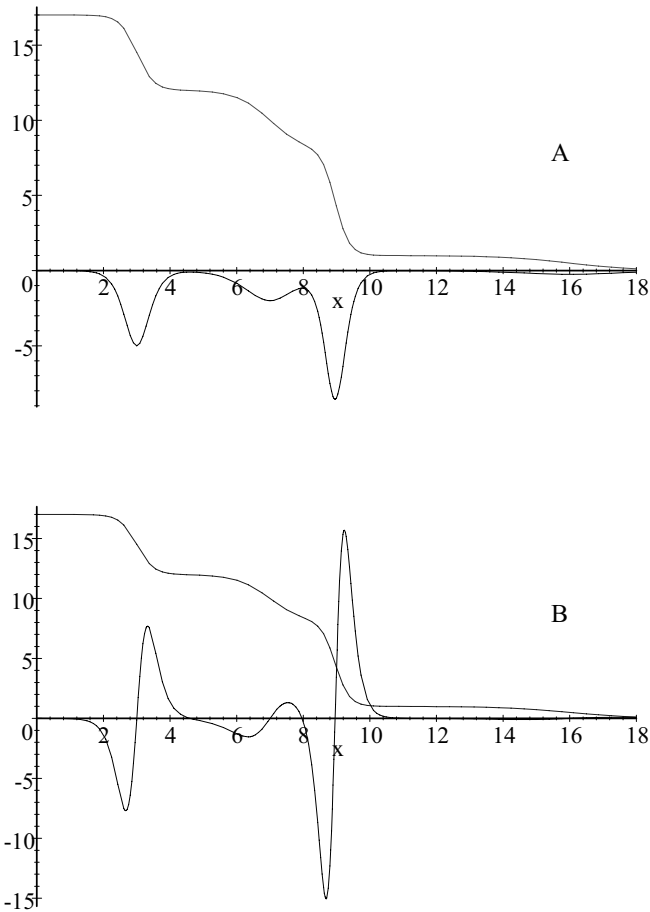


Figure 5. The overall function, obtained from the sum of the 4 functions previously described (dashed curve) and the first (A) and second (B) derivatives.

2.3.2. Logistic parametric fitting

For the fitting of data to a logistic function it is needed the calculation of values for the equation parameters. This task is usually performed by using a statistical software. In this case, the non linear regression and derivatives packages of the S-plus software.

The algorithm used for the non linear regression is:

$$y_i = m(x_i, \theta) + \varepsilon_i, i = 1, 2, \dots, n$$

where the response variable and the independent variable values are represented by y_i and x_i , respectively. θ is the parameters vector, that is estimated by least squares and ε_i are the errors, with normal distribution, mean zero and constant variance.

The residuals of the model are defined as:

$$e_i(\theta) = y_i - m(x_i; \theta), i = 1, 2, \dots, n$$

The parameters of the model were estimated by the non linear least squares method. The fundamentals of this method were described by Gay, D. M. [14]

The Levenberg-Marquart method routine for generation of the approximation sequence to the minimum point, based in the “trust region” algorithm, was used for the calculation of the parameter values that minimize that sum. This algorithm was discussed by Chambers, J. M., and Hastie, T. J. [4]. Its application to the computer calculation was described Dennis, J. E. et al. [7].

One of the problems that appear when fitting is to choose some starting points for the different parameters to estimate. To do this, one possibility consists in, by observation of the TGA trace, to try to estimate the inflexion. Since this method is not easy and requires previous expertise, we propose a method based in the idea of supposing that the data follow a logistic regression (Equation 3). So it is possible to fit the logit $Y(t)/w$ function to a straight line which y origin is a_i and which slope is b_i . The reason for this linear fitting is explained as follows:

$$Y(t) = wf(a + bt) = w \frac{\exp(a + bt)}{1 + \exp(a + bt)} \Rightarrow \frac{\frac{Y(t)}{w}}{1 - \frac{Y(t)}{w}} = \frac{Y(t)}{w - Y(t)} = \frac{\frac{\exp(a + bt)}{1 + \exp(a + bt)}}{\frac{1}{1 + \exp(a + bt)}} = \exp(a + bt)$$

So:

$$\text{logit}\left(\frac{Y(t)}{w}\right) = \log\left(\frac{\frac{Y(t)}{w}}{1 - \frac{Y(t)}{w}}\right) = a + bt$$

2.3.3. Application of the logistic regression to different cases

In order to validate the model in extreme situations, some TGA experiments exhibiting very different behaviours were considered. The first one corresponds to the hexahydrophthalic anhydride that underwent a typical evaporative process. It consisted in a single weight loss step with maximum weight loss rate at the end of the step [18]. The second one corresponds to the analysis of wood from Eucaliptus globulus. The wood is a very complex material where the main components are cellulose and lignin. Its thermal behaviour is quite complex and overlapped processes seem to be involved. Apparently, it decomposes in four main steps. Other complex cases considered were wood from Cupressus sempervirens and plasticized poly-(vinyl chloride).

Hexahydrophthalic anhydride case

In the case of a hexahydrophthalic anhydride experiment, since there is only one weight loss step, only one logistic function is needed to modelise the TGA trace. In other words, the equation that describes the overall process is

$$Y(t) = wf(a + bt)$$

The lineal fitting of Equation (7) to the TGA data, by least squares, gives the values for the a and b parameters, resulting the following expression that describes the behaviour of the hexahydroptalic anhydride in that experiment:

$$Y(t) = \frac{12.93 \exp(17.48 - 0.024t)}{1 + \exp(17.48 - 0.024t)}$$

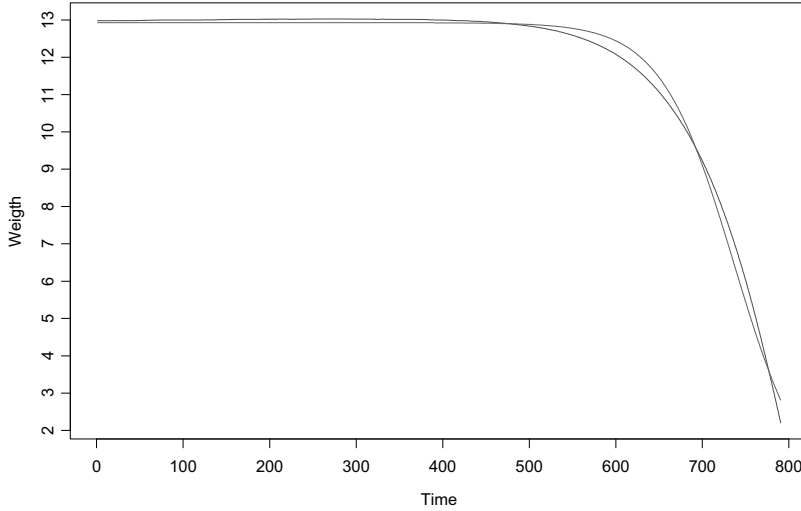


Figure 6. TGA trace obtained from a hexahydroptalic anhydride experiment.

The case of cupressus wood

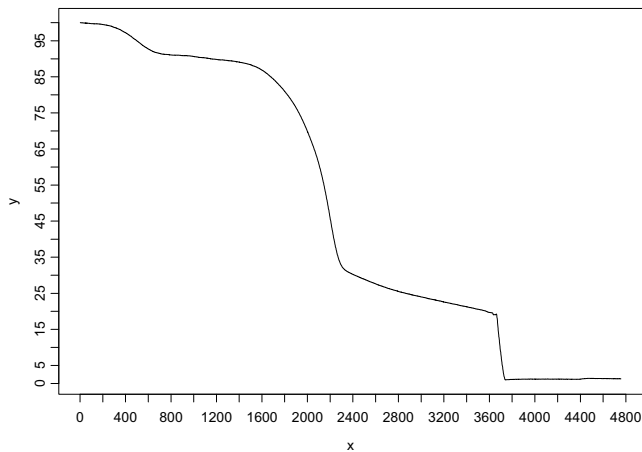


Figure 7. TGA plot obtained from a cupressus wood sample.

Linear fitting of different parts of the curve were performed in order to find the parameter values:

In order to do this, the $\text{logit}(y)$ function is plotted versus x and a line is fitted by the S-Plus software:

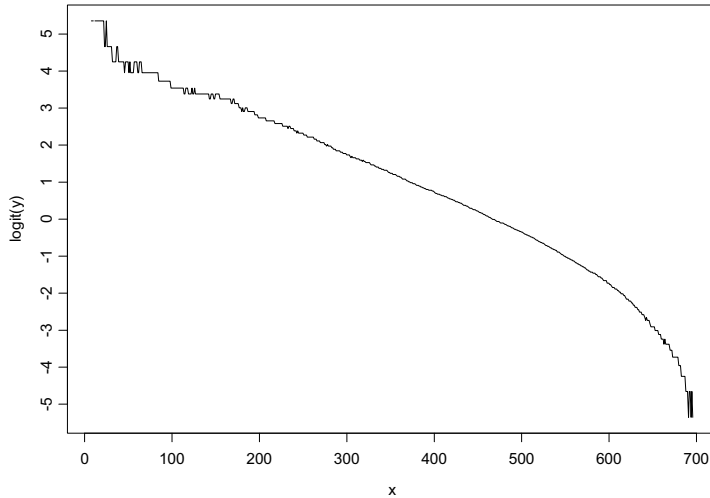


Figure 8. Plot of the $\text{logit}(y)$ function versus time in the range from 0 to 700 s.

The fitting was performed in two ranges of data. The first one is [0:700]. Since the neighbour values to 0 and 700 result in log 0, ten points will be suppresses in each end of the range. A line was fitted between 10 and 690, resulting in $w1=8.5$, $a1=5.12$, $b1=0.012$. These values were used to initiate the model.

The next range [700:1640], that includes a step, was operated in the same way, resulting the following values $a2=9.175879$, $b2=-0.004551135$ with 1631 total degrees of freedom and residual standard error= 0.7296343

Finally, the model was fitted with these starting values.

Parameter	Value	Std. Error	t value
w1	10.53520	0.0995712	105.8060
a1	3.79104	0.1033680	36.6750
b1	-0.00765	0.0001785	42.8834
w2	89.90570	0.0350401	2565.7900
a2	12.63650	0.0331148	381.5970
b2	-0.00571	0.0000151	378.0200

Fitting for the eucaliptus experiment

In this case four logistic components were assumed:

In this case, the fitting to obtain the starting values was performed in four ranges, giving the following values for the parameters of the model:

Parameter	value	Std. Error	t value
w1	13.04790	0.0579730	225.0690
a1	5.06769	0.0766370	66.1258
b1	-0.01132	0.0001576	71.8585
w2	41.09420	0.1888330	217.6220
a2	15.45890	0.0789307	195.8550
b2	-0.00851	0.0000429	198.0830
w3	22.53420	0.1765470	127.6390
a3	162.17000	3.3659800	48.1791
b3	-0.08569	0.0017780	48.1930
w4	23.19600	0.0503995	460.2440
a4	100.28700	1.2685400	79.0574
b4	-0.04103	0.0005184	79.1501

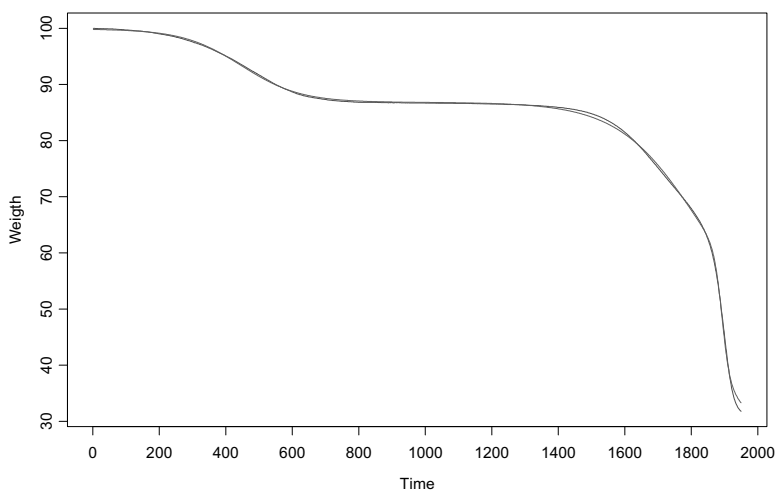


Figure 9. Plot of the original TGA trace compared to the estimated function.

Fitting in the case of PVC

In this case the fitting to obtain the starting values was performed in four ranges, resulting in the following equation:

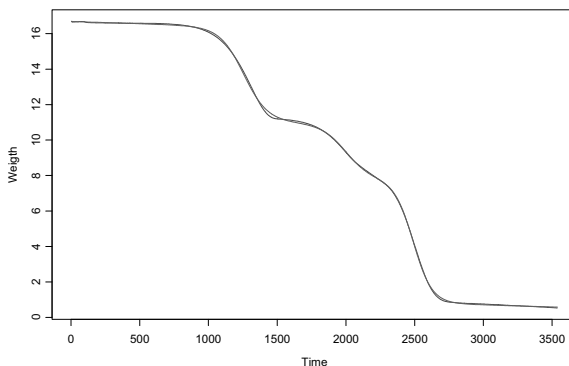


Figure 10. Fitting in the case of PVC.

$$2.287f(0.631 - 0.09t) + 5.276f(14.45 - 2.15t) + 3.061f(22.47 - 2.09t) + 6.86f(36.69 - 2.75t)$$

2.3.4. Physical meaning of the parameters

Once the fittings were performed in different cases it is clear that the $w_i(t)$ values represent the magnitude of each weight loss process. The b_i parameters have the meaning of sample volatilization rate, while the a_i value represents the scale.

2.4. Conclusions

1. This method allows for including at once the overall trace from a TGA experiment, while the classical methods can only be applied to a single step each time.
2. Overlapped degradation processes can be explained by this method. Since the existing models were thought to explain single processes, they generally fit very badly to overlapped processes.
3. It explains the thermal degradation of each component of the sample by a single function that may be easily understood from the physical point of view.
4. This model shows the contribution of each single degradation process to the overall process. It is very useful in order to improve thermal stability of materials.
5. It allows for measuring the statistical goodness of the fitting by signification contrast.
6. It allows applying classical kinetic models, like Arrhenius, to each of the single degradation functions. It is useful in order to compare with other materials in specific cases where some models proved to work well. Permite, para su comparación con materiales ya estudiados, la aplicación de modelos cinéticos clásicos del tipo Arrhenius a cada una de las funciones de degradación individuales.

7. It is easier to apply the classical kinetic models on the functions obtained by our method than on the raw TGA data, since the raw data contains noise that affects the derivative and integral estimations. In whose classical methods are based.
8. The asymptoticity is perfectly reproduced at the beginning and end of each degradative process.

3. Functional non-parametric model for materials discrimination by thermal analysis

3.1. Introduction

An important topic in Material Science is the classification of materials. The information obtained by thermo gravimetric analysis can be used to this aim. In this work, functional regression by nonparametric methods was used for the classification of different polymers. The method can be extended to any kind of material that can be analyzed by TGA.

Pattern recognition techniques deal with classification of observations in a finite number of classes (Watanabe, [30]).

It can be done by several parametric models, such as the discriminant analysis. Nevertheless, in the case of curves, the problem is functional and non parametric models are more suitable, since they take into account all the information from the sample (Ramsay and Silverman, [22]).

The method of classification proposed in this work is based in functional regression by nonparametric methods. Several PVC and wood samples were classified by this method. Finally, many simulated experiments were used to evaluate the accuracy of the method.

3.2. Nonparametric classification method

The nonparametric methods do not require previous estimation of any parameter. In this case, the kernel method was chosen. It is a nonparametric discrimination method that has been proved to work well in many cases (Ferraty and Vieu, [11]).

The nonparametric Bayes classification rule was used to classify the sample. It assigns a future observation to the highest probability class.

The different TGA curves, X_i , were taken as explanatory variable X_i , and the classes a sample of the response Y_i .

Considering a new TGA curve, obtained from a material to classify, the estimator of the posterior probability is given by:

$$\hat{p}_h^j(x) = \frac{\sum_{i=1}^n 1_{\{Y_i=j\}} K\left(\frac{\|x - X_i\|}{h}\right)}{\sum_{i=1}^n K\left(\frac{\|x - X_i\|}{h}\right)} \quad (20)$$

Equation (20) is a version of the Nadaraya-Watson estimator reported by Ferraty and Vieu, [11].

The L_1 norm will be used as distance between curves and h is the bandwidth, or smoothing parameter.

The classification rule is calculated from the estimator obtained in equation (20). This rule minimizes the probability of incorrect classification, that is:

$$d_h(x) = \arg \max_{0 \leq j \leq G} \{ \hat{p}_h^{(j)} \}$$

where $\hat{p}_h^{(j)}$ represents the estimation of the probability of the sample belonging to the j class.

The parameter smoothing h will be chosen that minimizes the probability of misclassifying a future observation. This bandwidth parameter will be taken as h_{CV} , that minimizes the following cross-validation function:

$$CV(h) = n^{-1} \sum_{i=1}^n 1_{\{Y_i \neq d_h^{-i}(X_i)\}}$$

where d_h^{-i} is the classification rule, built up without the i -th observation.

Finally, given a new sample and its TGA trace, denoted as x , the distances from this trace to the others will be calculated and $\hat{p}_h^{(j)}$ will be estimated for each class of material $j \in \{0, 1, 2, \dots, G\}$. The material will be assigned to the k class that maximizes $\hat{p}_h^{(j)}(x)$.

3.3. Application to PVC samples

The method of classification proposed was applied to a sample of 16 PVC items, plasticized in different degrees. The sample weight was about 35 mg in all the cases. The TGA experiment consisted in a heating ramp from 25 to 600 °C at 10 K/min followed by an isothermal step at 600 °C for 15 minutes. A 50 ml/min purge of air was kept along the experiment.

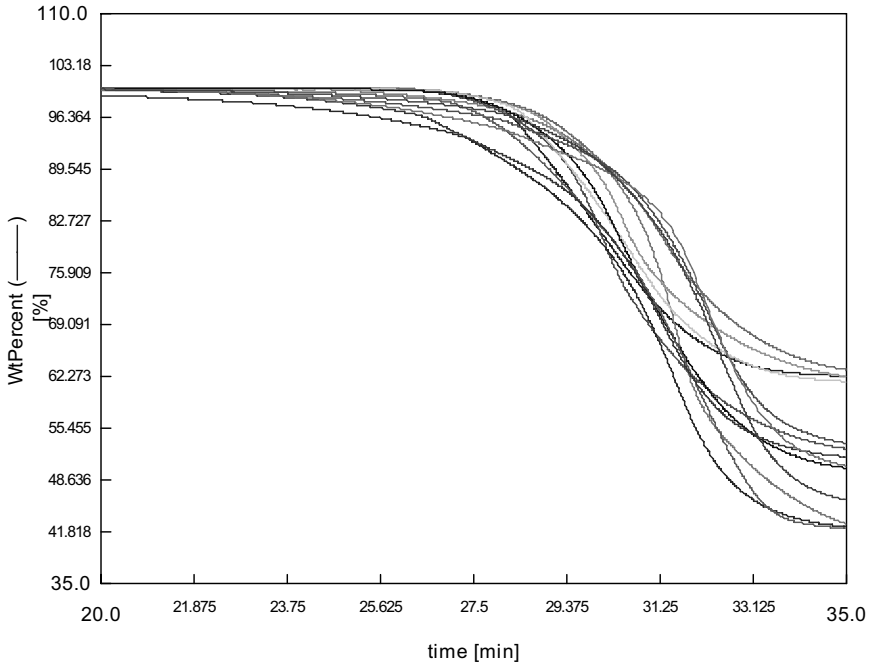


Figure 11. Overlay of sixteen TGA curves obtained from PVC.

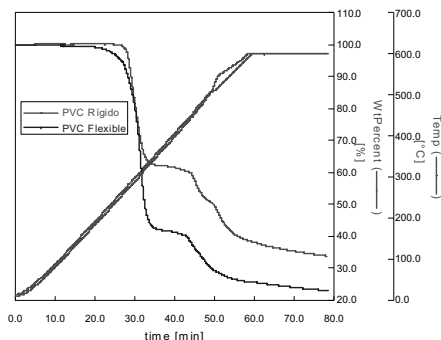


Figure 12. Overlay of two TGA traces, obtained from different samples of PVC.

Each sample was classified by keeping itself excluded from the reference population. A 99.4 % of correct classification was obtained by the application of the method proposed to the 16 PVC samples. It can be seen in Figure 13, which plots the cross-validation function.

3.4. Simulated experiments

A simulation study was performed in order to check the method. Three kinds of wood were chosen, since these materials are very much alike in composition and thermal behaviour. It is not easy to classify this kind of materials only by TGA experiments. From actual experiments of the three samples, two sets of experiments were simulated by a logistic mixture model. The simulation was performed for each of the three groups, using the function:

$$\varphi^{(r)}(x) = \sum_{j=1}^{k_r} w_j^{(k_r)} f(a_j^{(r)} + b_j^{(r)} x) \tag{21}$$

$$f(x) = \frac{\exp(x)}{1+\exp(x)}, \quad (r = 1,2,3).$$

The parameters for the model were simulated following a k_r -dimension Normal distribution. Two different situations were considered: parameters being independent and dependent.

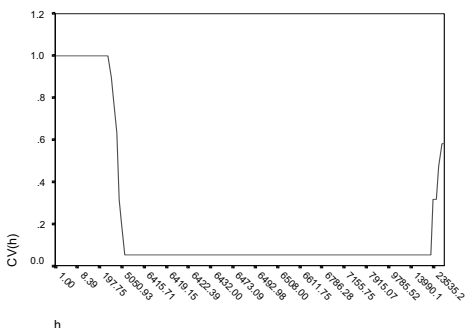


Figure 13. Plot of the cross-validation function against the smoothing parameter.

The first set of simulated experiments consisted of 90 TGA traces, whose probability to belong to each of the three groups was 1/3. The cross-validation bandwidth and the minimum of the cross-validation function were obtained from that simulated traces.

Then, a second set of 1000 traces was simulated, using the same probability than in the first set. Each curve was classified by the estimated non parametric rule of Bayes. The result of the classification was compared with the group from which the trace was simulated. The percent of the 1000 traces that were correctly classified was taken as an estimation of the probability of correct classification. The results show that the lower the variance of the model the larger the percent of correct classification, reaching 92 to 95 % correct classification for variances with values of 1/8 of the original variance. Generally, the percent of correct classification slightly increases in case of dependent data.

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