

Quantitatively modelling kinetics through a visual analysis of the derivative thermogravimetric curves: Application to biomass pyrolysis

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Abstract

Analytic relations are developed that directly link visually observable features of differential thermogravimetric (DTG) curves (e.g., peak temperature, height, width, skewness and conversion at the peak) to the parameters of chemical reaction kinetics models (e.g., activation energy and prefactor), which can be used to study the thermal decomposition of solid fuels. General expressions suitable for any reaction model are provided, as well as explicit expressions for n th order reactions with a rate constant given by the Arrhenius equation. This approach is illustrated for the pyrolysis of biomass, where it is found to provide a rapid and accurate estimate of the relative contributions of cellulose, hemicellulose, and lignin to the volatile yield, as well as their kinetic parameters. The method offers a simple way to obtain the model reaction kinetics parameters from thermogravimetric data and saves computing time by providing sensible initial values and bounds of the fit parameters.

Keywords: biomass pyrolysis, reaction kinetics, peak shape, deconvolution model

1. Introduction

Biomass is a promising renewable resource that can be thermally converted directly to heat or to other useful products like bio-oil, gas and char. Biomass pyrolysis consists of heating the biomass in the absence of oxygen, in order to obtain a range of valuable products that can be used to produce clean biofuels and biochemicals. This process is considered to be carbon neutral, and biomass, if sustainably harvested, is a readily available resource. These aspects make products derived from biomass an attractive alternative to fossil fuels, of which there is a depleting supply, and their burning contributes to global warming.

Biomass can be characterized in terms of its chemical, elemental and proximate analysis. Common values for the proximate analysis of lignocellulosic biomass are 5–10% moisture, less than 5% of ash, 10–20% fixed carbon, and

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10 70–80% of volatile content [1]. The main chemical components of biomass are hemicellulose, cellulose, and lignin;
11 their relative proportions vary across different types of biomass. They each undergo different thermal transformations
12 due to their specific chemical structure, and, therefore, their degradation occurs in distinct temperature ranges. Hemi-
13 cellulose is a branched polymer, usually represented by the molecule xylan ($C_5H_8O_4$), and its decomposition takes
14 place between 200 and 300°C. Cellulose is an unbranched polymer of glucose ($C_6H_{10}O_5$) that decomposes between
15 240 and 350°C. Lignin is an amorphous and complex polymer, decomposing between 250 and 500°C [6, 7]. It is
16 acknowledged that interactions between the components can affect their decomposition [2, 3, 4], but this is typically
17 assumed not to be significant [5].

18 Due to the heterogeneity of biomass and that its decomposition might comprise parallel and consecutive reactions,
19 only approximate reaction mechanisms can be drawn. To use it as an alternative to fossil fuels, research on the kinetics
20 of its thermochemical processes is needed to achieve high energy efficiency [8]. Research on biomass pyrolysis is
21 currently focused on both fundamental and practical aspects of the process, including intrinsic reaction kinetics and
22 heat and mass transfer at the particle and reactor scales, which are the main controlling processes to take into account
23 for reactor and process design, mainly focused on product yields distribution and prediction. Typically, at the early
24 stage of biomass pyrolysis, condensable (bio-oil) and non-condensable (gas) volatiles are released from the solid
25 biomass, then, if the condensable volatiles are not removed from the reaction zone, they can further react to form
26 more permanent gases [9].

27 The main operating conditions in biomass pyrolysis that affect the product yields are the heating rate, the maximum
28 temperature at which the biomass is held, and the residence time of the volatile in the reaction zone [10]. Depending
29 on the desired product, these parameters are adjustable to produce preferred end-products. In order to increase the
30 liquid yield, a high heating rate to a moderate temperature of about 500°C and a short residence time of the volatile,
31 in the order of seconds, that are subsequently quenched into bio-oil are required. The operating conditions may also
32 affect the composition of the bio-oil recovered from the condensable volatiles. Furthermore, smaller particle sizes
33 of feedstock in pyrolysis process also contribute to an increase in liquid yield [11, 12]. Kinetic analysis is often
34 used to elucidate the reaction mechanisms of biomass decomposition. A good reaction mechanism should be able to
35 predict biomass decomposition for a wide range of operating conditions and biomass types, in order to be coupled
36 with transport models and thus, scale up the process for industrial purposes.

37 Thermogravimetric analysis (TGA) is a widely used standard approach to study the thermal decomposition of
38 biomass. In TGA, a sample is subjected to a temperature program, and changes in the mass of the sample are recorded.
39 The differential thermogravimetric (DTG) curve describes the mass loss rate of the sample with temperature or time.
40 A DTG curve from biomass pyrolysis typically features several peaks, each of them corresponding to the individual

41 decomposition of each chemical component.

42 In analyzing a biomass sample from a single thermogravimetric run and treating the biomass as a homogeneous
43 material, the results cannot be generalized to other types of biomass or alternative process conditions.

44 A practical approach to increasing the applicability of an experiment to a wider range of biomass types is to
45 assume that the overall decomposition of a biomass sample can be described as a sum of the individual decomposition
46 of its main chemical components and assuming that there is no significant interactions between them [5].

47 A multi-component kinetic mechanism, comprises the individual decomposition behavior of each component, and
48 each reaction scheme can comprise one or more consecutive reactions, the power-law reaction model being the most
49 used. Detailed kinetic mechanisms often take into account intermediate reactions and product yields, for instance,
50 kinetic schemes with an intermediate step and schemes that comprise numerous consecutive reactions and predict
51 specific species in each product phase, like the ones by Ranzi et al. [13, 14].

52 As for the applicability of the kinetic parameters to a wider range of operating conditions, a possible solution is
53 to evaluate simultaneously thermogravimetric data from different TGA/DTG curves, obtaining one or more shared
54 kinetic parameters. With multi-component mechanisms, simultaneous evaluation of TGA/DTG curves becomes more
55 complex than dealing with a single component, and it can be carried out in several ways. For example, Gronli et
56 al. simultaneously fitted DTG curves from different types of biomass using the same heating rate, and determined a
57 single activation energy for all samples but different pre-exponential factors and component fractions [15]. In contrast,
58 Branca et al. used DTG data from the same type of biomass at different heating rates, and determined a single set of
59 kinetic parameters but different initial component fractions depending on the heating rate [16].

60 Wet chemistry techniques are generally employed for the determination of biomass composition, although it is
61 also known to be costly and time consuming, and the fractions may be altered in the process. Near infrared (NIR)
62 spectroscopy has been recently reported as an alternative approach to determine biomass composition, however, this
63 technique requires sophisticated equipment and can result in overlapping absorption peaks, making the identification
64 of components more difficult [17]. Deconvolution (or fitting) of TGA data from biomass pyrolysis is another approach
65 that has been studied to obtain the biomass composition [18, 19, 20, 21]. In this case the calculated composition
66 accounts for the volatile fractions of each component in biomass, having biomass over 80% of volatile matter on a
67 dry, ash-free basis [22]. The biomass composition, found through deconvolution of a DTG curve, is suitable to use in
68 combination with a multi-component kinetic mechanism, because the mechanism describes how the volatile fraction
69 of the biomass is released from the solid.

70 To distinguish between the individual component reactions within a DTG curve, the different characteristic reac-
71 tion peaks need to be deconvolved. A deconvolution based on a physical reaction kinetics model normally requires

72 an optimization algorithm and an initial estimate of the model parameters; in addition, the relative contribution of the
73 biomass components is needed if a multi-component mechanism is used. If the model is complex or has numerous
74 adjustable parameters, for many algorithms the initial estimates of the parameters should not be too different from
75 their optimal values; therefore, a good initial estimate of the parameters is paramount to achieve a meaningful fit.
76 These initial values would normally be estimated using the results from previous fits or from literature data, when
77 available. When a good initial estimate of the parameters is not available, evolutionary optimization algorithms, like
78 differential evolution, genetic algorithms [23] or particle swarm optimization [24] can be used. Evolutionary algo-
79 rithms do not require good starting values to find a global optimum and are typically initialized randomly; however,
80 these optimization algorithms can be very time-consuming.

81 Efforts have been made to relate the basic features of a DTG curve directly to parameters of reaction kinetics
82 models. Previous work has studied how changes in the order of reaction, activation energy, pre-exponential factor
83 and heating rate affect the shape of the mass loss and DTG curves [25]. The peak temperature is a parameter in the
84 Van-Krevelen approximation for the exponential integral of the Arrhenius equation [26], and it is also central in the
85 widely used model-free Kissinger method, able to extract kinetic parameters from DTG data at different heating rates
86 [27].

87 A method to calculate the kinetic parameters from a single DTG curve was developed by Kim et al., first using
88 the peak temperature and the height of peak [28], later improved by adding a third shape parameter, which is the
89 conversion at the peak temperature, to determine the reaction order assuming an n th-order reaction mechanism [29].
90 The effect on the DTG curves of different reaction mechanisms was analyzed and described by Dollimore et al. in
91 terms of their width at half-height and conversion at the peak temperature to obtain a correlation between the shape of
92 the DTG curve and kinetic mechanism [30].

93 In this work, we develop a method to estimate the parameters of a reaction kinetics model directly from the features
94 of a DTG curve, in particular, the peak temperature, height, width, skewness, as well as the conversion at the peak
95 temperature. The method saves computing time by reducing the number of iterations needed to fit experimental DTG
96 data and by providing sensible initial values and constraints to model parameters, independently of the optimization
97 method used and without the need of previous kinetic information on the process. Previous work in the literature that
98 relates the shape of the DTG curve with reaction kinetics relies on numerical analysis. The approach of this paper is
99 entirely analytical and provides a direct link between shape and reaction kinetics. Furthermore, it can be used with
100 any reaction model, such as a distributed activation energy model, as long as the number of model parameters does not
101 exceed the number of measurable shape parameters. In this case, a high number of shape parameters are included in
102 the method and can be used in any combination, although the expressions become increasingly complex. In addition,

103 it also allows a simple manner to screen reaction models to determine their applicability.

104 The remainder of this article is organized as follows. In the next section, the basic description of reaction kinetics
105 is quickly reviewed. Then, in Sec. 3, we present a simple approach to quantitatively characterize the shape of DTG
106 curves, and develop expressions that allow the calculation of the parameters of general reaction kinetic models. Ex-
107 plicit expressions are given for single-step n th-order reactions with rate constants given by the Arrhenius equation.
108 Some examples of the application of these expressions to experimental thermogravimetric data from the literature for
109 the pyrolysis of several types of biomass are given in Sec. 4 to help explain and exemplify the method. Finally, the
110 main findings and future directions of this work are summarized in Sec. 5.

111 2. Theory

112 2.1. Kinetics of biomass pyrolysis

113 Thermogravimetry has been widely used for the analysis of solid-state kinetics. From the first derivative of the
114 mass loss over time or temperature, the DTG curve is obtained. The DTG curve renders the rate of reaction, which
115 increases with temperature until it reaches a maximum, corresponding to the peak temperature. Figure 1a is an
116 example of experimental data obtained from thermogravimetric analysis, featuring a mass loss and a DTG curve,
117 which could be fitted to a model to determine the kinetic parameters and the chemical composition. From the DTG
118 curve, rather than with the TGA curve, it is easier to distinguish the different reactions corresponding to the different
119 peaks, despite the certain degree of overlapping. Observing the DTG curve in Figure 1a, there are some features
120 from a number of the peaks (i.e. peak temperature, width and height) that can be identified and easily estimated,
121 the rest of features can still be quantitatively approximated using the same units as in the axis of the DTG plot,
122 so a reasonable value could be given within the observed bounds. Most available kinetic models in the literature
123 use a rate law that follows the Arrhenius expression of temperature dependence. The Arrhenius equation has been
124 adapted from homogeneous reactions in gas/liquid phase to solid-state kinetics, and in the latter, it is observed that,
125 for a given reaction, instead of a single value of activation energy for the whole range of temperatures, the value of
126 the activation energy might vary as the reaction proceeds or depending on the experimental conditions [31]. In this
127 regard, various approaches have been explored, like employing different reaction models, distributed activation energy
128 methods (DAEM), iso-conversional methods and simultaneous fitting of thermogravimetric data at different heating
129 rates. When dealing with multi-component and/or multi-step mechanisms with overlapping reactions, simultaneous
130 non-linear fitting of data from different heating programs is advisable [32].

The decomposition of biomass is often expressed as a function of conversion $\alpha = (m_0 - m_t)/(m_0 - m_f)$, where m_0
is the sample initial weight, m_t is the weight at a time t , and m_f refers to the remaining mass when the process has

finished. The rate law of biomass pyrolysis is assumed to have the form

$$\frac{d\alpha}{dt} = k(T) f(\alpha), \quad (1)$$

131 where $d\alpha/dt$ is the reaction rate, $f(\alpha)$ represents the reaction model, T is the biomass temperature, and $k(T)$ is the
 132 rate constant. In decomposition reactions that occur in a kinetically controlled regime, it is reasonable to assume that
 133 the temperature of the biomass sample is uniform and equal to the temperature of the environment. Several reaction
 134 models may be used [35], for a first order reaction model, the rate of reaction depends only on the temperature and
 135 the amount of remaining unreacted sample $(1 - \alpha)$.

TG analysis is usually performed with small samples of up to 20 mg and a particle size no larger than $100 \mu\text{m}$ [5]. In the TG analyzer, the temperature of the reaction environment can be set constant in order to perform isothermal analysis or set into a dynamic mode, usually consisting of a constant heating rate of up to 100 K min^{-1} [36]. For non-isothermal analysis at a constant heating rate, the temperature varies with time according to

$$T = \beta t + T_0 \quad (2)$$

where β is the heating rate, and T_0 is the temperature of the biomass at the beginning of the process, usually at room temperature. The change of mass with respect to temperature is given by

$$\frac{d\alpha}{dT} = \frac{1}{\beta} k(T) f(\alpha). \quad (3)$$

For non-isothermal TGA experiments we need to fit the experimental data to a model in order to get the kinetic parameters, the fitting method is based on the least squares minimization of the difference between the experimental and calculated data. To calculate the reaction rate, we integrate Eq. (3):

$$g(\alpha) = \frac{A}{\beta} \bar{p}(T) \quad (4)$$

where A is a temperature independent parameter in the expression for the rate constant, and the functions $g(\alpha)$ and $\bar{p}(T)$ are defined as

$$g(\alpha) = \int_0^\alpha \frac{d\alpha'}{f(\alpha')} \quad (5)$$

and

$$\bar{p}(T) = \frac{1}{A} \int_{T_0}^T dT' k(T') \quad (6)$$

136 In general, the integral $\bar{p}(T)$ cannot be evaluated analytically and must be approximated or determined numerically.

137 In this section, the Arrhenius equation and its integration has been reviewed in order to help introduce the analytical
138 relations between the DTG peak shape and kinetics, presented in the following section.

139 3. Linking peak shape and reaction kinetics

140 Key features that characterize the shape of a peak in a DTG curve are the location of the peak T_p , the height of
141 the peak H_p , the width from the center to the left of the peak W_- , and from the center to the right of the peak W_+ at
142 a fraction θ of its height (see Figure 1b). Given these quantitative measures, the peak can be accurately represented
143 mathematically by the exponential-Gaussian hybrid (EGH) model [37], which is defined as

$$\alpha'_{EGH}(T) = \begin{cases} H_p \exp\left(-\frac{(T-T_p)^2}{2\sigma^2 + \tau(T-T_p)}\right) & \text{if } 2\sigma^2 + \tau(T - T_p) > 0 \\ 0 & \text{if } 2\sigma^2 + \tau(T - T_p) \leq 0 \end{cases} \quad (7)$$

144 This model was originally developed to deconvolve the wide variety of peak shapes that occur in chromatography
145 experiments. The parameters σ and τ are related to the widths W_- and W_+ as

$$\sigma^2 = -\frac{W_+ W_-}{2 \ln \theta} \quad (8)$$

$$\tau = -\frac{W_+ - W_-}{\ln \theta} \quad (9)$$

146 For a symmetric peak, $W_+ = W_-$, $\tau = 0$, and the EGH model reduces to a Gaussian peak model; in this case, the full
147 width at half maximum (FWHM) is equal to $2(2 \ln 2)^{1/2} \sigma \approx 2.35\sigma$, where σ would be the equivalent to the standard
148 deviation of a Gaussian distribution with the same curvature at the peak. In the EGH model, the value of σ depends
149 on the chosen height fraction of the peak, according to Eq. (8). When W_- is larger than W_+ , the curve is skewed to
150 the left, and τ is negative.

In order to relate the characteristics of the peak shape to the parameters of a reaction kinetics model, we perform

a Taylor series expansion of the natural logarithm of the reaction rate $\ln \alpha'(T)$ around the peak temperature T_p

$$\ln \alpha'(T) \approx [\ln \alpha'(T_p)] + \frac{1}{2}[\ln \alpha'(T_p)]''(T - T_p)^2 + \frac{1}{3!}[\ln \alpha'(T_p)]'''(T - T_p)^3 + \dots, \quad (10)$$

and compare this to the corresponding Taylor series expansion of the exponential-Gaussian hybrid $\ln \alpha'_{EGH}(T)$

$$\ln \alpha'_{EGH}(T) \approx \ln H_p - \frac{(T - T_p)^2}{2\sigma^2} + \frac{\tau}{4\sigma^4}(T - T_p)^3 + \dots. \quad (11)$$

Matching the expressions order by order, we obtain a set of relationships between the derivatives of the reaction rate at the peak temperature and the parameters that characterize the shape of the peak:

$$\ln \alpha'(T_p) = \ln H_p \quad (12)$$

$$[\ln \alpha'(T_p)]' = 0 \quad (13)$$

$$[\ln \alpha'(T_p)]'' = -\sigma^{-2} \quad (14)$$

$$[\ln \alpha'(T_p)]''' = \frac{3}{2} \frac{\tau}{\sigma^4}. \quad (15)$$

151 The conversion at the peak temperature can be determined from the relation

$$g(\alpha_p) = \frac{A}{\beta} \bar{P}(T_p). \quad (16)$$

152 Equations (12)–(16) provide the required constraints on the parameters of the reaction kinetics that need to be satisfied
 153 in order to reproduce the peak height H_p , the peak temperature T_p , the width of the peak σ , the peak skewness τ , and
 154 peak conversion α_p , respectively.

155 Figure 2 compares the Gaussian, EGH, and n -order reaction kinetics models for the same peak temperatures and
 156 same values of σ to show the difference between the skewness of the Gaussian and the Arrhenius curves, displaying
 157 the latter an asymmetric peak, and how good the EGH model can reproduce both models. The skewness to the left
 158 of the Arrhenius DTG curve is common in non-isothermal reactions where the reaction rate increases with time until
 159 the unreacted mass is too small to keep increasing and drops, and a skewness to the right would be characteristic of
 160 isothermal conditions [38].

The derivatives in Eq. (10) can be calculated for a given choice of rate constant $k(T)$ and reaction model $f(\alpha)$,

$$\ln \alpha'(T_p) = \ln k(T_p) + \ln f(\alpha_p) \quad (17)$$

$$[\ln \alpha'(T_p)]' = [\ln k(T_p)]' + [\ln f(\alpha_p)]' \alpha'(T_p) \quad (18)$$

$$[\ln \alpha'(T_p)]'' = [\ln k(T_p)]'' + [\ln f(\alpha_p)]'' [\alpha'(T_p)]^2 \quad (19)$$

$$[\ln \alpha'(T_p)]''' = [\ln k(T_p)]''' + \sigma^{-2} [\ln k(T_p)]' + [\ln f(\alpha_p)]''' [\alpha'(T_p)]^3. \quad (20)$$

161 The relationships presented up to this point are general and valid for any expression of $k(T)$ and $f(\alpha)$.

162 3.1. *n*th-order reaction model

163 In this section, we focus our attention to reaction models of the general form

$$f(\alpha) = (1 - \alpha)^n, \quad (21)$$

where n is the order of the reaction. The integral of the n th order reaction model is

$$g(\alpha) = [(1 - \alpha)^{1-n} - 1]/(n - 1) \quad (22)$$

Using this in Eq. (4) gives the conversion as an explicit function of the temperature

$$\alpha = 1 - \left[1 + (n - 1) \frac{A}{\beta} \bar{p}(T) \right]^{-1/(n-1)} \quad (23)$$

The corresponding expressions for the derivatives of the rate of reaction assuming an n th-order reaction model are

$$\ln \alpha'(T_p) = [\ln \bar{k}(T_p)]' - \frac{n}{n-1} \ln \left(1 + (n-1) \frac{A}{\beta} \bar{p}(T_p) \right) = \ln H \quad (24)$$

$$[\ln \alpha'(T_p)]' = [\ln \bar{k}(T_p)]' - n \frac{A}{\beta} \bar{k}(T_p) \left[1 + (n-1) \frac{A}{\beta} \bar{p}(T_p) \right]^{-1} = 0 \quad (25)$$

$$[\ln \alpha'(T_p)]'' = [\ln \bar{k}(T_p)]'' - \frac{1}{n} \{[\ln \bar{k}(T_p)]'\}^2 = -\sigma^{-2} \quad (26)$$

$$[\ln \alpha'(T_p)]''' = [\ln \bar{k}(T_p)]''' - [\ln \bar{k}(T_p)]'' [\ln \bar{k}(T_p)]' + \frac{n-2}{n^2} \{[\ln \bar{k}(T_p)]'\}^3 = \frac{3}{2} \frac{\tau}{\sigma^4} \quad (27)$$

$$\alpha_p = 1 - \left[1 + (n-1) \frac{A}{\beta} \bar{p}(T_p) \right]^{-1/(n-1)} \quad (28)$$

164 Equation (24) is related to the height of the peak, Eq. (25) is related to the position of the peak, Eqs. (26) and (27)

165 can be used in Eqs. (14) and (15) to obtain expressions for σ and τ . Equation (28) gives the conversion at T_p , which
 166 might be useful to identify the best reaction model or, in the case of n th-order reaction models, the order of reaction
 167 [39].

168 The expressions derived up to this point, are general expressions that could be applied to any rate constant for an
 169 n th-order reaction model. Below we specialize to the case where the rate constant is given by the Arrhenius equation.

170 3.1.1. Arrhenius rate constant

171 One common expression for the rate constant $k(T)$ is the Arrhenius equation

$$k(T) = A e^{-E/(RT)} \quad (29)$$

where A is the pre-exponential factor, E is the activation energy, and R is the universal gas constant. The corresponding derivatives are

$$\begin{aligned} \ln \bar{k}(T) &= -\frac{T_E}{T} \\ [\ln \bar{k}(T)]' &= \frac{T_E}{T^2} \\ [\ln \bar{k}(T)]'' &= -2\frac{T_E}{T^3} \\ [\ln \bar{k}(T)]''' &= 6\frac{T_E}{T^4}. \end{aligned}$$

172 where $T_E = E/R$.

The resulting expressions for the peak width and peak asymmetry parameters for n th-order reactions are

$$\sigma = n^{1/2} \frac{T_p^2}{T_E} \left(1 + 2n \frac{T_p}{T_E} \right)^{-\frac{1}{2}} \quad (30)$$

$$\tau = \frac{2}{3}(n-2) \frac{T_p^2}{T_E} \left[1 + 2n \left(\frac{T_p}{T_E} \right) \right]^{-2} \left[1 + \frac{2n^2}{n-2} \left(\frac{T_p}{T_E} \right) + \frac{6n^2}{n-2} \left(\frac{T_p}{T_E} \right)^2 \right] \quad (31)$$

173 It is interesting to note that the peak width and asymmetry for this reaction kinetics model are dictated by the activation
 174 energy and the order of the reaction; they are independent of the pre-exponential factor of the Arrhenius equation.
 175 The T_p ranges for hemicellulose, cellulose and lignin will be located within the decomposition ranges already given
 176 in Sec. 1, and accordingly to the given ranges of typical activation energies of biomass pyrolysis [40], T_E would vary
 177 for hemicellulose between 9622 and 13952 K, cellulose between 2345 and 34400 K, and lignin between 2165 and

178 7818 K.

From knowledge of E and n , the pre-exponential factor can be determined from Eq. (25), which leads to

$$A = \beta \frac{1}{n} \left(\frac{T_E}{T_p^2} \right) e^{T_E/T_p} \left[1 - \frac{(n-1)}{n} \left(\frac{T_E}{T_p^2} \right) e^{T_E/T_p} \bar{p}(T_p) \right]^{-1}. \quad (32)$$

179 From this expression it can also be observed that the pre-exponential factor carries the effect of the heating rate.

The height of the DTG peak can be determined from Eq. (24)

$$H = \frac{A}{\beta} e^{-T_E/T_p} \left[1 + (n-1) \frac{A}{\beta} \bar{p}(T_p) \right]^{-n/(n-1)}. \quad (33)$$

180 Figure 3 shows how good the curve characteristics of the EGH model translate into the Arrhenius n th-order model
181 for a range of given values of σ and τ . As an example of application, the program used to generate this figure can
182 be found as a supplementary material. Both curves are fitted at half height and at that point they perfectly match,
183 however, they slightly differ at the base of the curve. Figure 4 shows a comparison, using the EGH model, of three
184 different values of τ for a given value of T_p , σ , height and heating rate, and it reflects how the value of τ is related to
185 the skewness of the curve, the more negative is τ , the more skewed is the curve; the chosen values of τ are negative
186 representing a curve skewness to the left. Figure 5 shows in which way the EGH parameters translate into the n th-
187 order Arrhenius ones (n , E , and A), for given values of heating rate, T_p and σ , and changing values of τ ; the three
188 kinetic parameters decrease with a more negative τ , meaning that the values of the kinetic parameters decrease as the
189 curve is more skewed to the left.

190 3.1.2. Estimation of the biomass relative composition for n th-order

The fraction of each component that can be determined from a DTG curve is their corresponding contribution to the volatiles released. The height of the peaks is related to the component fractions, for a $d\alpha/dT$ peak, according to

$$x = H \frac{\beta}{A} e^{T_E/T_p} \left[1 + (n-1) \frac{A}{\beta} \bar{p}(T_p) \right]^{-n/(1-n)} \quad (34)$$

191 In this section, mathematical relationships have been given between parameters that characterize the shape of a peak
192 in a DTG curve and the parameters of an n -order reaction kinetics model. In Sec. 3.2, we adapt the found relationships
193 for a first order reaction model.

194 3.2. First-order reaction model and Arrhenius rate constant

For a first-order reaction model, $n = 1$, and $f(\alpha) = (1 - \alpha)$. The expressions for σ , τ , and the pre-exponential factor found for n th-order given in Sec. 3.1 simplify to

$$\sigma \approx \frac{T_p^2}{T_E} \quad (35)$$

$$\tau \approx -\frac{2}{3} \frac{T_p^2}{T_E} \quad (36)$$

$$A = \beta \frac{T_E}{T_p^2} e^{T_E/T_p}. \quad (37)$$

195 It is worth noting that this expression for the pre-exponential factor is the same as in Kissinger method [41, 42] with
196 its corresponding form.

Assuming an Arrhenius rate constant, the integral $\bar{p}(T)$ in Eq. (4) would be defined as $\bar{p}(T) = T_E p(T_E/T)$, where

$$p(y) = - \int_y^{T_E/T_0} dy \frac{e^{-y}}{y^2}. \quad (38)$$

For first order, the integral in Eq. (22) is now modified to $g(\alpha) = -\ln(1 - \alpha)$, therefore the expression for conversion is

$$(1 - \alpha) = \exp \left[- \left(\frac{T_E}{T_p} \right)^2 e^{T_E/T_p} p(T_E/T) \right] \quad (39)$$

Incorporating this expression, as well as the Arrhenius rate constant and the expressions found for σ and A into Eq. (3), we obtain the following integrated form of the reaction rate, which is for a first order reaction model using an Arrhenius reaction rate

$$\frac{d\alpha}{dT} = - \exp \left[\frac{T_p}{\sigma} - \frac{T_p^2}{\sigma T} - \left(\frac{T_p}{\sigma} \right)^2 e^{T_p/\sigma} p(T_E/T) \right] \sigma^{-1} \quad (40)$$

The parameters for the peak shape can be converted to the parameters for the kinetics model with Eq. (41) and Eq. (42):

$$E = R \frac{T_p^2}{\sigma} \quad (41)$$

$$A = \frac{\beta}{\sigma} e^{T_p/\sigma} \quad (42)$$

197 According to these expressions, E and A are inversely proportional to σ , and their values increase with increasing T_p .

The height of the peak is particularly useful when dealing with multi-component mechanisms, as explained in Sec. 3.2.1. The height of the peak is found when $T = T_p$:

$$H_{p,i} = \exp \left[- \left(\frac{T_{p,i}}{\sigma} \right)^2 e^{T_{p,i}/\sigma_i} p(T_E/T_{p,i}) \right] x_i \beta \sigma_i^{-1} \quad (43)$$

198 3.2.1. Estimation of the biomass relative composition for first order

The relative contribution of cellulose, hemicellulose, and lignin to the volatile yield can be estimated from the peak heights H_p of a DTG curve. For a multi-component kinetic mechanism, the total decomposition of the biomass is a sum of the decomposition of its components

$$\frac{d\alpha}{dt} = \sum_{i=1}^n x_i \frac{d\alpha_i}{dt} \quad (44)$$

where x_i is the fraction of component i . From the height equation, Eq. (43), the component fraction is given by

$$x_i = \frac{H_{p,i} \sigma_i}{\beta \exp \left[- \left(\frac{T_{p,i}}{\sigma_i} \right)^2 e^{T_{p,i}/\sigma_i} p(T_{E,i}/T) \right]} \quad (45)$$

199 If fitting the experimental data, the composition calculated can be used as an initial estimation for the components
200 fractions, to be optimized along with the values of T_p and σ .

201 3.3. Kinetic analysis of experimental data from different heating rates

Thermogravimetric data from the same biomass sample, will have different peak positions depending on the heating rate. When considering the decomposition of a single component, the kinetic parameters, in principle, could be calculated by adapting the methodology presented previously to deal with different heating rates, by equating the expression for the pre-exponential factor, found in Eq. (32) for an n th-order reaction, from two different heating rates

$$-\ln \frac{\beta}{\beta^*} = \frac{T_E}{T_p^*} \left(\frac{T_p^*}{T_p} - 1 \right) + 2 \ln \left(\frac{T_p^*}{T_p} \right) \quad (46)$$

and a simplified form with only peak shape parameters for first-order

$$-\ln \frac{\beta}{\beta^*} = \frac{T_p^*}{\sigma^*} \left(\frac{T_p^*}{T_p} - 1 \right) + 2 \ln \left(\frac{T_p^*}{T_p} \right) \quad (47)$$

202 where the asterisk corresponds to parameters of the reference conditions. Ideally, given a single peak, for each pair of
203 heating rates, the same activation energy should be found, an example of the application of this equation is given in

204 Sec. 4.2.1.

205 4. Results and Discussion

206 To illustrate the utility of the expressions developed in the previous sections, specific examples of the kinetic
207 analysis of thermogravimetric data from biomass pyrolysis are provided, where the reactions are assumed to proceed
208 with an Arrhenius rate constant and to be either a first-order or n th-order model. In Sec. 4.1, experimental data
209 from a single heating rate experiment are analyzed, and, in Sec. 4.2, data from several heating rates are evaluated
210 simultaneously. For both cases, the biomass is initially treated as a single component (e.g., pure cellulose). Then it is
211 considered to be a combination of its main chemical components (i.e. hemicellulose, cellulose and lignin).

212 4.1. Kinetic analysis of experimental data from a single heating rate

213 4.1.1. Single-component mechanism

214 Experimental TGA data of cellulose pyrolysis at 10 K min^{-1} [34] has been used as an example of kinetic analysis
215 by directly calculating the kinetic parameters from only the measurable features of the peak shape, without the need of
216 performing a fit. The shape parameters are measured on the DTG curve of conversion versus temperature, which area
217 is one, therefore T_p , σ , τ , and height and conversion at the T_p are quantitatively estimated. The kinetic parameters
218 for a first order reaction with an Arrhenius rate constant are E and A , and for an n th-order reaction model are E , A ,
219 and n . The number of peak shape parameters to be measured depends on the number of kinetic parameters to be
220 calculated for the chosen reaction model. For the peak in Figure 6, the observed shape parameters are $T_p = 632.4 \text{ K}$,
221 $W_- = 22.9 \text{ K}$, $W_+ = 15.6 \text{ K}$, $H = 0.024 \text{ K}^{-1}$ and $\alpha = 0.616$; the corresponding values of σ and τ are 16.0 K and
222 -10.4 K , respectively.

223 Assuming a first-order reaction model, Eqs. (41) and (42) are used to directly calculate the values of the kinetic
224 parameters, resulting in $E = 206.3 \text{ kJ mol}^{-1}$ and $A = 1.2 \times 10^{15} \text{ s}^{-1}$, similar to the literature values of $E = 237 \text{ kJ mol}^{-1}$
225 and $A = 1 \times 10^{18} \text{ s}^{-1}$ [34]. In this case, the shape parameters that are constrained are T_p and σ . Assuming an n th-
226 order reaction model, Eqs. (28), (30), (31), (32), and (33) can be used to calculate the kinetic parameters. Each
227 expression constrains one of the measurable parameters, but in this case only three of the expressions are needed in
228 order to calculate E , A , and n . In this example, we choose to constrain T_p , σ , and τ , and, consequently, we obtain
229 $E = 194.9 \text{ kJ mol}^{-1}$, $A = 1.3 \times 10^{14} \text{ s}^{-1}$, and $n = 0.94$. Calculating the height ($H_p = 0.024 \text{ K}^{-1}$) and conversion
230 ($\alpha = 0.625$) from the resulting kinetic values, it can be noticed that the resulting height coincides with the measured
231 one, but the conversion is slightly bigger than observed, which makes sense if we compare it with the given range of
232 conversion values for a first-order reaction model [39] and we see that our resulting order of reaction is slightly smaller

233 than one, and conversion at the peak is slightly bigger than the literature value. The height and conversion could
 234 have also been used to calculate the kinetic parameters, instead of σ and τ ; the only difference is which observable
 235 characteristics of the peak shape we want to predict with more accuracy.

236 4.1.2. Multi-component mechanism

Experimental thermogravimetric data of beech wood pyrolysis at 5 K min^{-1} [15] were used as an example of for
 the deconvolution of a multi-component system in order to determine not only the reaction kinetics, but also the
 composition of the sample. The fitting procedure of a DTG curve consists of performing a least-squares minimization
 of the difference between the experimental and predicted rate of mass loss:

$$\text{O.F.} = \sum_{k=1}^n \left[\left(\frac{d\alpha}{dT} \right)_{\text{calc}} - \left(\frac{d\alpha}{dT} \right)_{\text{exp}} \right]^2 \quad (48)$$

$$\left(\frac{d\alpha}{dT} \right)_{\text{calc}} = \sum_{i=1}^3 x_i \frac{d\alpha_i}{dT} \quad (49)$$

237 For a first-order reaction model, the rate of reaction is calculated with Eq. (40) with respect to time. The input
 238 values are the initial estimates for the parameters to adjust, determined by direct observation of the DTG curve, these
 239 parameters are the $T_{p,i}$, σ_i , and $H_{p,i}$, where i denotes each component reaction. The biomass relative composition x_i
 240 is estimated with Eq. (45), and the parameters to be optimized are $T_{p,i}$, σ_i , and x_i . The resulting values of $T_{p,i}$ and σ_i
 241 can be used in Eqs. (41) and (42) to obtain the values of activation energy and pre-exponential factor.

242 The peak temperatures were allowed to vary in a range of 50 K from the selected temperature, this range depends
 243 on how distinguishable the curve peaks are and their level of overlapping, in this case, for cellulose and hemicellulose,
 244 their T_p was fairly identifiable but not so much for lignin. The σ was allowed to vary between 0.5σ and 1.5σ .
 245 Individual bounds for a particular component can be specified, but yet, provided a good initial guess, the ones that
 246 are clearly around the value given, will tend to remain there independently of the size of the range. The resulting
 247 fit is shown in Figure 7, and the resulting kinetic parameters and composition in Table 1. For deconvolution with
 248 the n th-order reaction model, the fit is done directly with the EGH model, setting the bounds for τ and σ as $(0.5\tau$
 249 $\text{ to } 1.5\tau)$ and $(0.5\sigma \text{ to } 1.5\sigma)$, respectively. In this case, the initial conditions are the resulting parameters found from
 250 the deconvolution with a first-order reaction. The resulting kinetic parameters for the first-order reaction model are
 251 similar to those reported in the literature, and the calculated kinetic parameters for the n th-order reaction model, which
 252 can also be found in Table 1, are not far from the values determined for the first-order reaction.

253 The determined relative contribution of the biomass components is between 34.6% and 41.2% hemicellulose,
 254 between 45.8 and 55.7% cellulose and between 9.7 and 13% lignin. The reported composition, experimentally de-

Table 1: Resulting kinetic parameters from deconvolution of beech wood as in Figure 7.

	first-order	n th-order	literature [15]
$E_{HCE} / \text{kJ mol}^{-1}$	97	114.8	100
A_{HCE} / s^{-1}	2.4×10^6	1.5×10^8	4.3×10^6
$E_{CELL} / \text{kJ mol}^{-1}$	231.5	191.5	236
A_{CELL} / s^{-1}	1.7×10^{17}	6.3×10^{13}	3.8×10^{17}
$E_{LIG} / \text{kJ mol}^{-1}$	45.9	74.3	46
A_{LIG} / s^{-1}	5.5	1.5×10^3	4
n_{HCE}	1	1.3	1
n_{CELL}	1	0.83	1
n_{LIG}	1	1.2	1
χ^2	0.011	0.005	

Table 2: Resulting kinetic parameters from simultaneous deconvolution of macadamia nutshell as in Figure 9.

	first-order	n th-order	literature [45]
$E_{HCE} / \text{kJ mol}^{-1}$	125.9	131.4	132.2–150.6
A_{HCE} / s^{-1}	1.9×10^9	6.6×10^9	2.9×10^9 – 1.8×10^{11}
$E_{CELL} / \text{kJ mol}^{-1}$	182.1	173.1	221.2–265.7
A_{CELL} / s^{-1}	6.2×10^{12}	1.1×10^{12}	8.9×10^{15} – 8.2×10^{19}
$E_{LIG} / \text{kJ mol}^{-1}$	59.2	72.7	62.8–74.5
A_{LIG} / s^{-1}	1.3×10^2	1.9×10^3	2.7×10^2 – 1×10^4
n_{HCE}	1	1.1	1
n_{CELL}	1	0.88	1
n_{LIG}	1	1.2	1
χ^2	0.036	0.028	

255 terminated for beech [43], is 78% of holocellulose (hemicellulose + cellulose), 20% of lignin, and 2% of extractives
 256 on a dry basis. Taking into account that lignin is the major contributor to char formation [44], the calculated results
 257 seem consistent with the experimental data, since in the volatile there is a bigger fraction of holocellulose than in the
 258 raw biomass. In the case of deconvolution of DTG data from a single heating rate, it has been found that there is no
 259 significant difference or improvement when considering an n th-order reaction model instead of a first-order one.

260 Fitting is a mathematical procedure that does not obey any thermo-chemical law, and sometimes results that are
 261 not in agreement with what we already know about the thermal behavior of the material can be obtained. For instance,
 262 in the case example, we need to make sure that the peak temperatures and decomposition ranges are in agreement
 263 with what is reported in the literature for similar conditions. The advantage of using the peak shape methodology, is
 264 the easy estimation of the initial values to be adjusted, and that their constraints have the same units as in the DTG
 265 curve axis. For instance, if we observe that the predicted decomposition does not take place in a temperature range in
 266 agreement with the ranges reported in the literature, the fit could be adjusted by shifting the T_p towards the reported

267 range or modifying the bounds to widen them, symmetrically or not.

268 4.2. Kinetic analysis of experimental data from several heating rates

269 4.2.1. Single-component mechanism

270 Experimental data from cellulose pyrolysis at different heating rates [34, 46, 47, 48, 49, 19, 21, 20, 50] were used
271 to exemplify how the peak shape method can be used to find a single set of kinetic parameters across all the DTG
272 experimental data. For DTG data from a single component at different heating rates, Eq. (47) could be used to find
273 a single set of kinetic parameters, as rendered in Figure 8a, where each line in the plot corresponds to a different
274 activation energy. The peak shape parameter obtained from the experimental data is the T_p from DTG curves of
275 cellulose pyrolysis at different heating rates, and is represented by black dots. For the sake of clarification, the red
276 crosses correspond to calculated data derived for $E = 100 \text{ kJ mol}^{-1}$ at three different heating rates, their DTG curves
277 are shown in Figure 8b.

278 If the experimental data would display an ideal behavior, as the calculated data, all points would fall on the
279 same line, defining which is the specific activation energy for cellulose, but as can be observed from the figure, the
280 experimental data does not behave as expected.

281 There could be several explanations for the fact that the experimental data does not define a unique activation
282 energy. One explanation is related to the comparability of the experimental data, it is possible that the different
283 cellulose sources used by the different authors, and the different experimental conditions might have had an impact
284 on the distribution of the peak temperatures, or that the experiments might be governed by transport phenomena
285 rather than being kinetically controlled; furthermore, it is also possible that the single-step and first-order reaction
286 model does not satisfactorily render the complexity of the decomposition process. The experimental points allow the
287 delineation of a range of activation energies, but to find a single set of kinetic parameters suitable across the range
288 of studied temperatures, a simultaneous evaluation of thermogravimetric data at different heating rates is considered
289 necessary and will be discussed in Sec. 4.2.2.

In Figure 8a, at the bottom, the width of the peak is plotted with respect to the heating rate. From both plots in
Figure 8a, it can be observed that T_p and σ increase proportionally with the heating rate, following the expression

$$\frac{\sigma}{\sigma^*} = \left(\frac{T_p}{T_p^*} \right)^2 \quad (50)$$

290 In the following section, we use the peak shape method to perform a simultaneous evaluation of DTG data from
291 several heating rates with a multi-component mechanism.

292 4.2.2. Multi-component mechanism

293 Experimental data from pyrolysis of macadamia nut shell are taken from the literature [45] to serve as an example
 294 of simultaneous deconvolution of several DTG curves at different heating rates, each of them featuring three main
 295 peaks corresponding to hemicellulose, cellulose and lignin. The choice of the reference curve is arbitrary. From four
 296 DTG curves of biomass pyrolysis performed at heating rates of 5, 10, 20, and 30 K min⁻¹, the one at 10 K min⁻¹ was
 297 selected to be a reference curve. This simultaneous fitting is suitable for single and multi-component decomposition
 298 mechanisms, but in the following example, we are going to consider a multi-component mechanism, the more complex
 299 of the two.

300 The input parameters for a first-order reaction model are $T_{p,i}^*$, σ_i^* and $H_{p,i}^*$, where the asterisk indicates that the
 301 properties belong to the reference curve. The initial values for the peak temperature and width are estimated by
 302 direct observation of the DTG curve, and the initial estimation of the composition comes from applying Eq. (45) to
 303 the reference curve. From the fitting, a single composition and a single set of kinetic parameters able to render the
 304 biomass decomposition, taking into account the impact of different heating rates, is obtained.

The fitting procedure is similar to the one applied in Sec. 4.1.2 for a single heating rate. The difference in this case
 is that a reference curve is chosen, and the rest of curves at the different heating rates are calculated with Eq. (47) with
 respect to the reference. In this way, only the kinetic parameters for the reference curve, $T_{p,i}^*$, σ_i^* and x_i^* , need to be
 adjusted to minimize the objective function

$$\text{O.F.} = \sum_{k=1}^n \left[\left(\frac{d\alpha}{dT} \right)_{\text{calc}} - \left(\frac{d\alpha}{dT} \right)_{\text{exp}} \right]^2 \quad (51)$$

$$\left(\frac{d\alpha}{dT} \right)_{\text{calc}} = \sum_{j=1}^4 \sum_{i=1}^3 x_i^{(j)} \frac{d\alpha_i^{(j)}}{dT} \quad (52)$$

305 where j denotes the different heating rates, and i denotes the components in the biomass.

306 The bounds for T_p are 50 K on each side of the chosen temperature value, the range is large due the fact that for
 307 hemicellulose and lignin the peaks are overlapped and difficult to identify, the lower bound for σ is 0.5 of the initial
 308 value, and the upper bound is 1.5 times the initial value. The resulting fit can be found in Figure 9 and the resulting
 309 kinetic parameters in Table 2.

310 Deconvolution of the DTG curve with an n th-order reaction mechanism was also carried out, and the results are
 311 reported in Table 2. Similar to the deconvolution performed in Sec. 4.1.2, no significant improvement in the fit was
 312 found by using an n th-order reaction model rather than the simpler first-order model. The estimated composition
 313 of the biomass is 27.1% hemicellulose, between 51.7 and 53.4% cellulose, and between 19.5 and 21.1% lignin. In
 314 comparison with the experimentally estimated raw material composition [51], the fraction of cellulose and hemicel-

315 lulose is larger with a lower fraction of lignin, like in the previous example given in Sec. 4.1.2. The calculated kinetic
316 parameters are similar to but slightly differ from the reported literature ranges, which might be due to the assumption
317 of only three components and leaving out extractives.

318 The reliability of the calculated kinetic parameters depends on the initial values and bound of the fit parameters,
319 the suitability of the chosen kinetic mechanism and the quality of the experimental data, meaning that the experimental
320 conditions should ensure that the process takes place in a kinetically controlled regime.

321 **5. Conclusions**

322 In this paper, we develop a method to estimate the parameters of a reaction kinetics model, directly from the
323 shape of the derivative thermogravimetric (DTG) curve. It is suitable for single or multi-component mechanisms
324 involving single-step reactions. The present work comprehensively encompasses the measurable shape parameters
325 of the DTG curve of biomass pyrolysis and from the study of chromatography peaks reported in the literature, by
326 deriving mathematical expressions that directly link the peak shape with kinetics. The shape parameters reported
327 in this work can be selected and used in any combination, according to the number of required kinetic parameters
328 specific for each reaction model. This gives the flexibility to decide which are the decomposition characteristics that
329 we want to predict with more accuracy, and also to assume different rate constants and reaction models.

330 In the specific examples of application included in this work, an Arrhenius rate constant and a first/*n*th-order reac-
331 tion model are used, which requires two/three kinetic parameters to be determined. The results of the deconvolution
332 examples, show how the shape method allows for an easy estimation of the initial values of the parameters, which
333 can be obtained by direct observation of the DTG curve. Furthermore, the bounds of the parameters can also be
334 defined from direct observation, in order to improve the fit or reduce the convergence time. When dealing with single-
335 component mechanisms, in which the DTG curve displays a single peak, the kinetic parameters can be calculated by
336 directly applying the expressions that link the peak shape parameters with the reaction kinetics, without the need to
337 fit. For multi-component mechanisms in which the DTG displays multiple peaks, the goodness of the fit relies on
338 the precision of the initial values and bounds of the fit parameters, and their estimation depends on the overlapping
339 degree of the peaks. The resulting kinetic parameters and contribution fractions of the biomass main components,
340 could then be used as the initial values of the key kinetic parameters and provide reasonable constraints in order to
341 reduce the computational cost of more elaborate fitting procedures. To improve the fit for the given examples, other
342 components could be included in the kinetic mechanism, such as extractives, and differing reaction models from the
343 *n*th-order could be considered. The present method for the kinetic analysis of thermogravimetric data could also be
344 applied to other similar thermal reactions from which we can obtain a DTG curve, such as a drying process or the

345 decomposition of other polymers or solid fuels.

346 **Supplementary material**

347 Program from Figure 3 written in Python 2.7.

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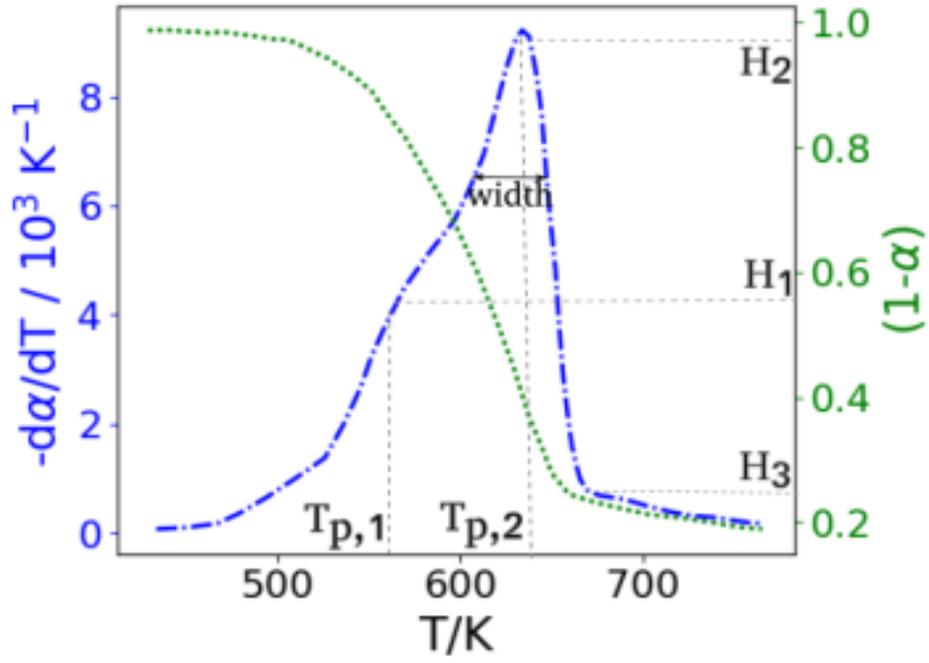
351 **Nomenclature**

352	α	Conversion fraction
353	β	Heating rate (K s^{-1})
354	σ	Width of the peak as in a Gaussian model (K)
355	θ	Fraction of the peak height
356	τ	Related to the asymmetry of the peak (K)
357	χ^2	chi-square
358	x_i	Contribution fraction of the component i to the volatile yield
359	A	Pre-exponential factor (s^{-1})
360	E	Activation energy (kJ mol^{-1})
361	$g(\alpha)$	Integral of the differential conversion versus the reaction model
362	H_p	Height of the peak at the peak temperature (s^{-1} or K^{-1})
363	k	Rate constant (s^{-1})
364	m_0	Initial mass (units of mass)
365	m_f	Final mass of the sample (units of mass)
366	m_t	Mass of the sample at a given time (units of mass)
367	$p(y)$	Exponential integral of the Arrhenius equation
368	R	Universal gas constant ($8.314 \cdot 10^{-3} \text{ kJ K}^{-1} \text{ mol}^{-1}$)
369	T_E	Auxiliary parameter, E/R (K)
370	T_p	Peak temperature, temperature at the maximum rate of reaction (K)
371	W_-	Width from the center to the left of the peak (K)
372	W_+	Width from the center to the right of the peak (K)
373	RMS	Root mean square

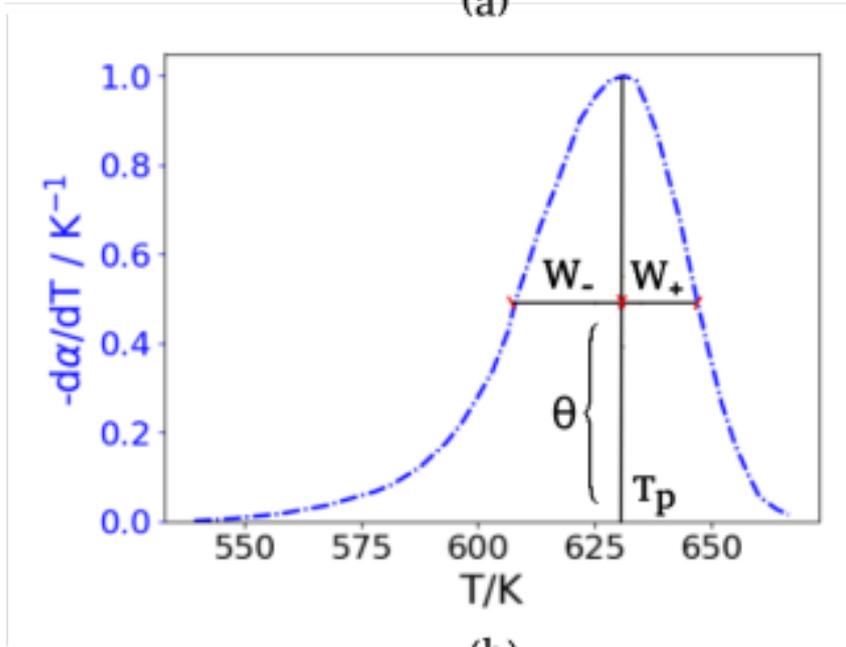
- 374 [1] A. Molino, V. Larocca, S. Chianese, D. Musmarra, Biofuels production by biomass gasification: A review, *Energies* 11 (4) (2018) 811.
375 doi:10.3390/en11040811.
376 URL <http://dx.doi.org/10.3390/en11040811>
- 377 [2] S. Wang, X. Guo, K. Wang, Z. Luo, Influence of the interaction of components on the pyrolysis behavior of biomass, *J. Anal. Appl. Pyrolysis*
378 91 (1) (2011) 183–189. doi:10.1016/j.jaap.2011.02.006.
- 379 [3] P. Giudicianni, G. Cardone, G. Sorrentino, R. Ragucci, Hemicellulose, cellulose and lignin interactions on arundo donax steam assisted
380 pyrolysis, *J. Anal. Appl. Pyrolysis* 110 (Supplement C) (2014) 138 – 146. doi:10.1016/j.jaap.2014.08.014.
- 381 [4] J. Yu, N. Paterson, J. Blamey, M. Millan, Cellulose, xylan and lignin interactions during pyrolysis of lignocellulosic biomass, *Fuel* 191 (Sup-
382 plement C) (2017) 140 – 149. doi:10.1016/j.fuel.2016.11.057.
- 383 [5] C. Koufopoulos, A. Lucchesi, G. Maschio, Kinetic modelling of the pyrolysis of biomass and biomass components, *Can. J. Chem. Eng.* 67 (1)
384 (1989) 9. doi:10.1002/cjce.5450670111.
- 385 [6] P. Harmsen, W. Huijgen, L. Bermudez, R. Bakker, Literature review of physical and chemical pretreatment processes for lignocellulosic
386 biomass, Tech. rep., Wageningen UR Food & Biobased Research (2010).
- 387 [7] J. S. Tumuluru, C. T. Wright, R. D. Boardman, R. J. Hess, S. Sokhansanj, Review on biomass torrefaction process and product properties
388 and design of moving bed torrefaction system model development, in: 2011 Louisville, Kentucky, August 7-10, 2011, American Society of
389 Agricultural and Biological Engineers, 2011, p. 1.
- 390 [8] T. Martí-Rosselló, J. Li, L. Lue, Kinetic models for biomass pyrolysis., *Archives of Industrial Biotechnology* 1 (1).
- 391 [9] P. Basu, *Biomass Gasification, Pyrolysis and Torrefaction: Practical Design and Theory*, Elsevier Science, 2013.
- 392 [10] P. Basu, Chapter 3 - Pyrolysis and Torrefaction, Academic Press, Boston, 2010, book section 3, pp. 65–96.
- 393 [11] A. Demirbas, G. Arin, An overview of biomass pyrolysis, *Energy Sources* 24 (5) (2002) 471–482. doi:10.1080/00908310252889979.
- 394 [12] A. Bridgwater, Principles and practice of biomass fast pyrolysis processes for liquids, *J. Anal. Appl. Pyrolysis* 51 (1) (1999) 3 – 22.
395 doi:10.1016/S0165-2370(99)00005-4.
- 396 [13] E. Ranzi, A. Cuoci, T. Faravelli, A. Frassoldati, G. Migliavacca, S. Pierucci, S. Sommariva, Chemical kinetics of biomass pyrolysis, *Energy*
397 *Fuels* 22 (6) (2008) 4292–4300. doi:10.1021/ef800551t.
- 398 [14] E. Ranzi, P. E. A. Debiagi, A. Frassoldati, Mathematical modeling of fast biomass pyrolysis and bio-oil formation. note i: Kinetic mechanism
399 of biomass pyrolysis, *ACS Sustainable Chemistry & Engineering* 5 (4) (2017) 2867–2881. doi:10.1021/acssuschemeng.6b03096.
- 400 [15] M. G. Grønli, G. Várhegyi, C. Di Blasi, Thermogravimetric analysis and devolatilization kinetics of wood, *Ind. Eng. Chem. Res.* 41 (17)
401 (2002) 4201–4208. doi:10.1021/ie0201157.
- 402 [16] C. Branca, A. Albano, C. Di Blasi, Critical evaluation of global mechanisms of wood devolatilization, *Thermochim Acta* 429 (2) (2005)
403 133–141. doi:10.1016/j.tca.2005.02.030.
- 404 [17] X. Li, C. Sun, B. Zhou, Y. He, Determination of hemicellulose, cellulose and lignin in moso bamboo by near infrared spectroscopy, *Sci. Rep.*
405 5 (2015) 17210. doi:10.1038/srep17210.
- 406 [18] L. Burhenne, J. Messmer, T. Aicher, M.-P. Laborie, The effect of the biomass components lignin, cellulose and hemicellulose on {TGA} and
407 fixed bed pyrolysis, *J. Anal. Appl. Pyrolysis* 101 (2013) 177 – 184. doi:10.1016/j.jaap.2013.01.012.
- 408 [19] M. Carrier, A. Loppinet-Serani, D. Denux, J.-M. Lasnier, F. Ham-Pichavant, F. Cansell, C. Aymonier, Thermogravimetric anal-
409 ysis as a new method to determine the lignocellulosic composition of biomass, *Biomass Bioenergy* 35 (1) (2010) 298–307.
410 doi:10.1016/j.biombioe.2010.08.067.
- 411 [20] V. Cozzani, A. Lucchesi, G. Stoppato, G. Maschio, A new method to determine the composition of biomass by thermogravimetric analysis.,
412 *Can. J. Chem. Eng.* 75 (1) (1997) 6. doi:10.1002/cjce.5450750120.

- 413 [21] K. Singh, M. Risse, K. C. Das, J. Worley, Determination of composition of cellulose and lignin mixtures using thermogravimetric analysis, *J.*
414 *Energy Res. Technol.* 131 (2). doi:10.1115/1.3120349.
- 415 [22] T. Reed, A. Das, Handbook of biomass downdraft gasifier engine system.
- 416 [23] A. I. Ferreiro, M. Rabaal, M. Costa, A combined genetic algorithm and least squares fitting procedure for the estimation of the kinetic
417 parameters of the pyrolysis of agricultural residues, *Energy Conversion and Management* 125 (2016) 290 – 300, sustainable development of
418 energy, water and environment systems for future energy technologies and concepts. doi:https://doi.org/10.1016/j.enconman.2016.04.104.
419 URL <http://www.sciencedirect.com/science/article/pii/S0196890416303648>
- 420 [24] L. Xu, Y. Jiang, L. Wang, Thermal decomposition of rape straw: Pyrolysis modeling and kinetic study via particle swarm optimization,
421 *Energy Conversion and Management* 146 (2017) 124 – 133. doi:https://doi.org/10.1016/j.enconman.2017.05.020.
422 URL <http://www.sciencedirect.com/science/article/pii/S019689041730451X>
- 423 [25] J. H. Flynn, L. A. Wall, General treatment of the thermogravimetry of polymers, *J. Res. Nat. Bur. Stand.* 70 (6) (1966) 487–523.
424 doi:10.6028/jres.070a.043.
- 425 [26] D. W. Van Krevelen, K. Te Nijenhuis, Properties of polymers: their correlation with chemical structure; their numerical estimation and
426 prediction from additive group contributions, Elsevier, 2009.
- 427 [27] H. E. Kissinger, Variation of peak temperature with heating rate in differential thermal analysis, *J. Res. Nat. Bur. Stand.* 57 (4) (1956) 217–221.
428 doi:10.6028/jres.057.026.
- 429 [28] S. Kim, J. K. Park, Characterization of thermal reaction by peak temperature and height of dtg curves, *Thermochimica Acta* 264 (1995) 137
430 – 156. doi:https://doi.org/10.1016/0040-6031(95)02316-T.
431 URL <http://www.sciencedirect.com/science/article/pii/S004060319502316T>
- 432 [29] S. Kim, E.-S. Jang, D.-H. Shin, K.-H. Lee, Using peak properties of a dtg curve to estimate the kinetic parameters of the pyrolysis reaction:
433 application to high density polyethylene, *Polym. Degrad. Stab.* 85 (2) (2004) 799–805. doi:10.1016/j.polymdegradstab.2004.03.009.
- 434 [30] D. Dollimore, T. Evans, Y. Lee, F. Wilburn, Correlation between the shape of a TG/DTG curve and the form of the kinetic mechanism which
435 is applying, *Thermochimica Acta* (2) 249–257. doi:10.1016/0040-6031(92)85081-6.
- 436 [31] S. Vyazovkin, Kinetic concepts of thermally stimulated reactions in solids: a view from a historical perspective, *Int. Rev. Phys. Chem.* 19 (1)
437 (2000) 45–60. doi:10.1080/014423500229855.
- 438 [32] S. Vyazovkin, A. K. Burnham, J. M. Criado, L. A. Pérez-Maqueda, C. Popescu, N. Sbirrazzuoli, Ictac kinetics committee recommendations
439 for performing kinetic computations on thermal analysis data, *Thermochim. Acta* 520 (1) (2011) 1–19. doi:10.1016/j.tca.2011.03.034.
- 440 [33] G. Várhegyi, Aims and methods in non-isothermal reaction kinetics, *J. Anal. Appl. Pyrolysis* 79 (1) (2007) 278–288.
441 doi:10.1016/j.jaap.2007.01.007.
- 442 [34] M. J. Antal, G. Várhegyi, E. Jakab, Cellulose pyrolysis kinetics: revisited, *Ind. Eng. Chem. Res.* 37 (4) (1998) 1267–1275.
443 doi:10.1021/ie970144v.
- 444 [35] A. Khawam, D. R. Flanagan, Solid-state kinetic models: basics and mathematical fundamentals, *J. Phys. Chem. B* 110 (35) (2006) 17315–
445 17328, pMID: 16942065. doi:10.1021/jp062746a.
- 446 [36] J. Blondeau, H. Jeanmart, Biomass pyrolysis at high temperatures: Prediction of gaseous species yields from an anisotropic particle, *Biomass*
447 *Bioenergy* 41 (2012) 107–121. doi:10.1016/j.biombioe.2012.02.016.
- 448 [37] K. Lan, J. W. Jorgenson, A hybrid of exponential and gaussian functions as a simple model of asymmetric chromatographic peaks, *J.*
449 *Chromatogr. A* 915 (1) (2001) 1 – 13.
- 450 [38] J. López-Beceiro, A. Álvarez-García, T. Sebio-Puñal, S. Zaragoza-Fernández, B. Álvarez-García, A. Díaz-Díaz, J. Janeiro, R. Artiaga,
451 Kinetics of thermal degradation of cellulose: Analysis based on isothermal and linear heating data, *BioResources* 11 (3).

- 452 [39] C. Haixiang, L. Naian, Z. Weitao, Critical study on the identification of reaction mechanism by the shape of TG/DTG curves, *Solid State*
453 *Sciences* (4) 455–460. doi:10.1016/j.solidstatesciences.2009.12.007.
- 454 [40] C. Di Blasi, Modeling chemical and physical processes of wood and biomass pyrolysis, *Prog. Energy Combust. Sci.* 34 (1) (2008) 47–90.
- 455 [41] H. E. Kissinger, Reaction kinetics in differential thermal analysis, *Anal. Chem.* 29 (11) (1957) 1702–1706. doi:10.1021/ac60131a045.
- 456 [42] R. L. Blaine, H. E. Kissinger, Homer kissinger and the kissinger equation, *Thermochim. Acta* 540 (2012) 1–6. doi:10.1016/j.tca.2012.04.008.
- 457 [43] C. Di Blasi, C. Branca, A. Santoro, R. A. P. Bermudez, Weight loss dynamics of wood chips under fast radiative heating, *J. Anal. Appl.*
458 *Pyrolysis* 57 (1) (2001) 77–90. doi:10.1016/s0165-2370(00)00119-4.
- 459 [44] B. Cagnon, X. Py, A. Guillot, F. Stoeckli, G. Chambat, Contributions of hemicellulose, cellulose and lignin to the mass and the porous
460 properties of chars and steam activated carbons from various lignocellulosic precursors, *Bioresour. Technol.* 100 (1) (2009) 292 – 298.
- 461 [45] T. Xavier, T. Lira, M. Schettino Jr, M. Barrozo, A study of pyrolysis of macadamia nut shell: Parametric sensitivity analysis of the ipr model,
462 *Braz. J. Chem. Eng.* 33 (1) (2016) 115–122. doi:10.1590/0104-6632.20160331s00003629.
- 463 [46] H. Zhou, Y. Long, A. Meng, S. Chen, Q. Li, Y. Zhang, A novel method for kinetics analysis of pyrolysis of hemicellulose, cellulose, and
464 lignin in tga and macro-tga, *RSC Advances* 5 (34) (2015) 26509–26516. doi:10.1039/c5ra02715b.
- 465 [47] Y.-C. Lin, J. Cho, G. A. Tompsett, P. R. Westmoreland, G. W. Huber, Kinetics and mechanism of cellulose pyrolysis, *J. Phys. Chem. C*
466 113 (46) (2009) 20097–20107. doi:10.1021/jp906702p.
- 467 [48] S. Wang, Q. Liu, K. Wang, X. Guo, Z. Luo, K. Cen, T. Fransson, Study on catalytic pyrolysis of manchurian ash for production of bio-oil,
468 *Int. J. Green Energy* 7 (3) (2010) 300–309. doi:10.1080/15435071003796111.
- 469 [49] K. M. Isa, S. Daud, N. Hamidin, K. Ismail, S. A. Saad, F. H. Kasim, Thermogravimetric analysis and the optimisation of bio-
470 oil yield from fixed-bed pyrolysis of rice husk using response surface methodology (rsm), *Ind. Crops Prod.* 33 (2) (2011) 481–487.
471 doi:10.1016/j.indcrop.2010.10.024.
- 472 [50] S. Wang, Q. Liu, Z. Luo, L. Wen, K. Cen, Mechanism study on cellulose pyrolysis using thermogravimetric analysis coupled with infrared
473 spectroscopy, *Front. Energy Power Eng. China* 1 (4) (2007) 413–419. doi:10.1007/s11708-007-0060-8.
- 474 [51] M. Antal, S. G. Allen, X. Dai, B. Shimizu, M. S. Tam, M. Grønli, Attainment of the theoretical yield of carbon from biomass, *Ind. Eng.*
475 *Chem. Res.* 39 (2000) 4024–. doi:10.1021/ie000511u.



(a)



(b)

Figure 1: (a) Pyrolysis of a wood sample at 10 K min^{-1} . The blue line is the mass loss curve, and the green line is the DTG curve [33]; T_p is the peak temperature, and H is the peak height. (b) Pyrolysis of cellulose at 10 K min^{-1} [34]; W is the width from the center to the side of the peak.

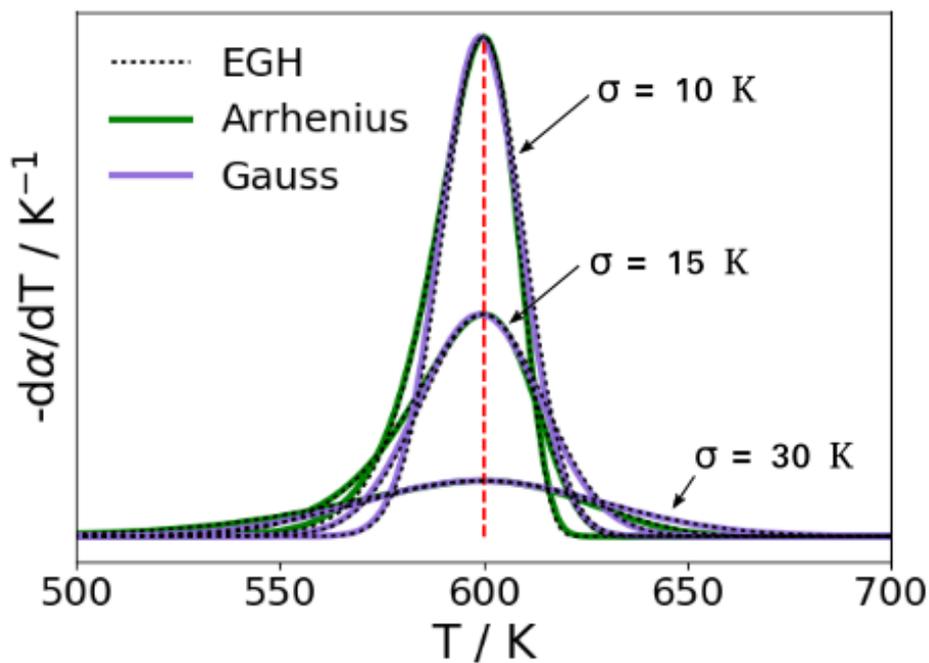


Figure 2: Comparison of peaks at $T_p = 600$ K and at different values of σ for a Gaussian distribution, an Arrhenius first-order model with the calculated kinetic parameters for $\sigma = 10$ K of $E = 300.0$ kJ mol $^{-1}$, $A = 9.5 \times 10^{23}$ s $^{-1}$ and RMS = 0.06%, for $\sigma = 15$ K of $E = 200.0$ kJ mol $^{-1}$, $A = 1.3 \times 10^{15}$ s $^{-1}$ and RMS = 0.03%, for $\sigma = 30$ K of $E = 100.0$ kJ mol $^{-1}$, $A = 1.3 \times 10^6$ s $^{-1}$ and RMS = 0.0%, and the EGH model corresponding to the Gaussian distribution with $\tau = 0$ and corresponding to the Arrhenius first-order model with $\tau = -6$ K and RMS = 0.01% for $\sigma = 10$ K, $\tau = -8.6$ K and RMS = 0.01% for $\sigma = 15$ K, and $\tau = -14.6$ K and RMS = 0.01% for $\sigma = 30$ K.

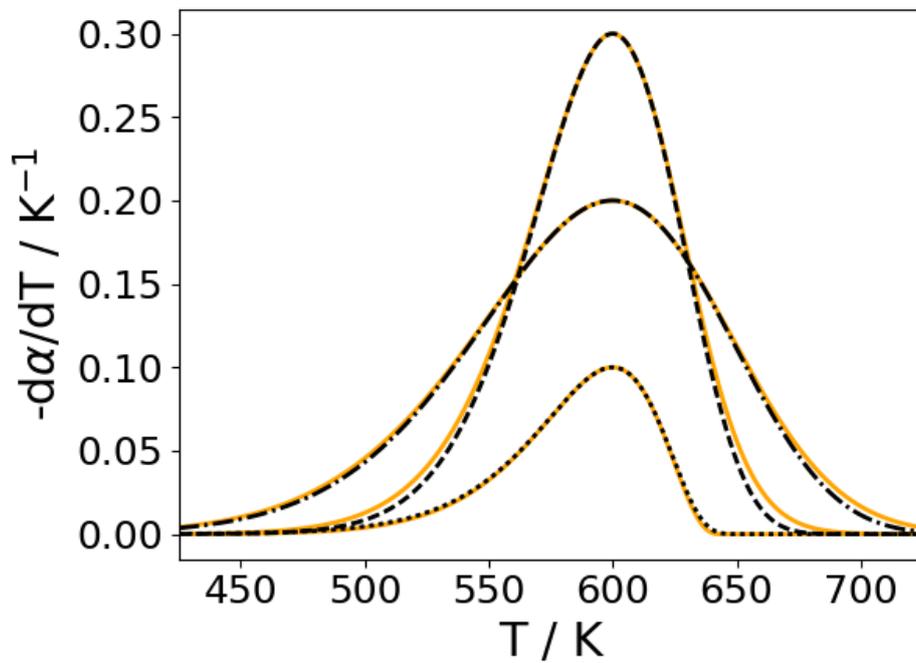


Figure 3: Peaks comparison of EGH model and n th-order Arrhenius at 20 K min^{-1} and $T_p = 600 \text{ K}$. Discontinuous line: EGH model, dashed-line corresponds to $H_p = 0.3 \text{ K}^{-1}$, $\sigma = 30 \text{ K}$ and $\tau = -10 \text{ K}$, dash-dot line $H_p = 0.2 \text{ K}^{-1}$, $\sigma = 50 \text{ K}$ and $\tau = -15 \text{ K}$, and dotted-line $H_p = 0.1 \text{ K}^{-1}$ with, $\sigma = 25 \text{ K}$ and $\tau = -20 \text{ K}$. Solid line: calculated Arrhenius n th-order, the calculated parameters corresponding to the EGH curve in dashed-line are $E = 103.3 \text{ kJ mol}^{-1}$, $A = 1.1 \times 10^7 \text{ s}^{-1}$, $n = 1.2$ and a RMS = 6.0%, for the dash-dot line $E = 57.9 \text{ kJ mol}^{-1}$, $A = 6.9 \times 10^2 \text{ s}^{-1}$, $n = 1.1$ and a RMS=5.1%, and for the dotted line $E = 100.9 \text{ kJ mol}^{-1}$, $A = 7.0 \times 10^6 \text{ s}^{-1}$, $n = 0.8$ and a RMS=0.0%.

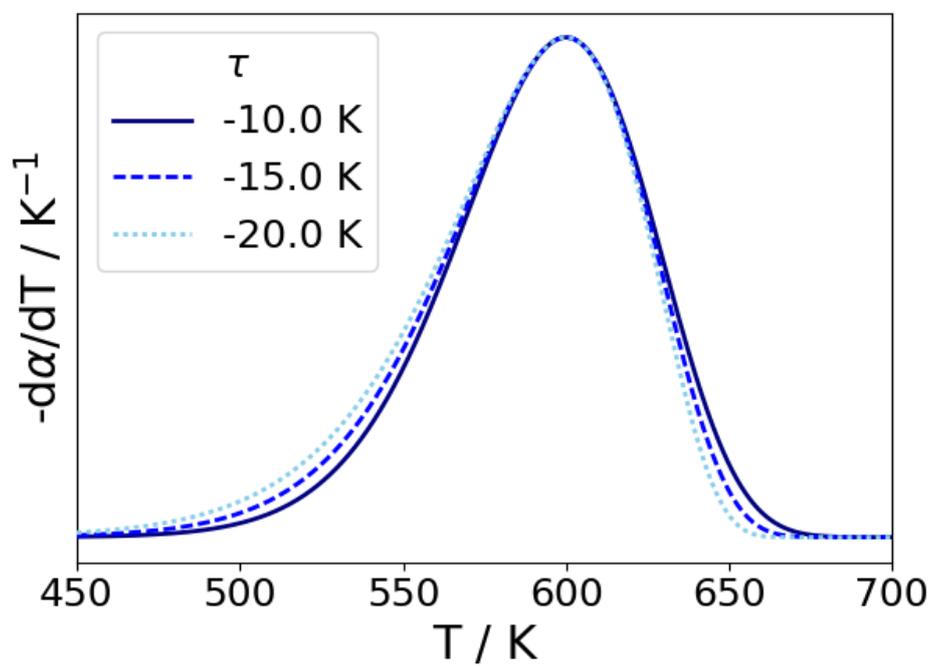


Figure 4: EGH model peaks comparison at 20 K min^{-1} , $T_p = 600 \text{ K}$ and $\sigma = 30 \text{ K}$ for different values of τ .

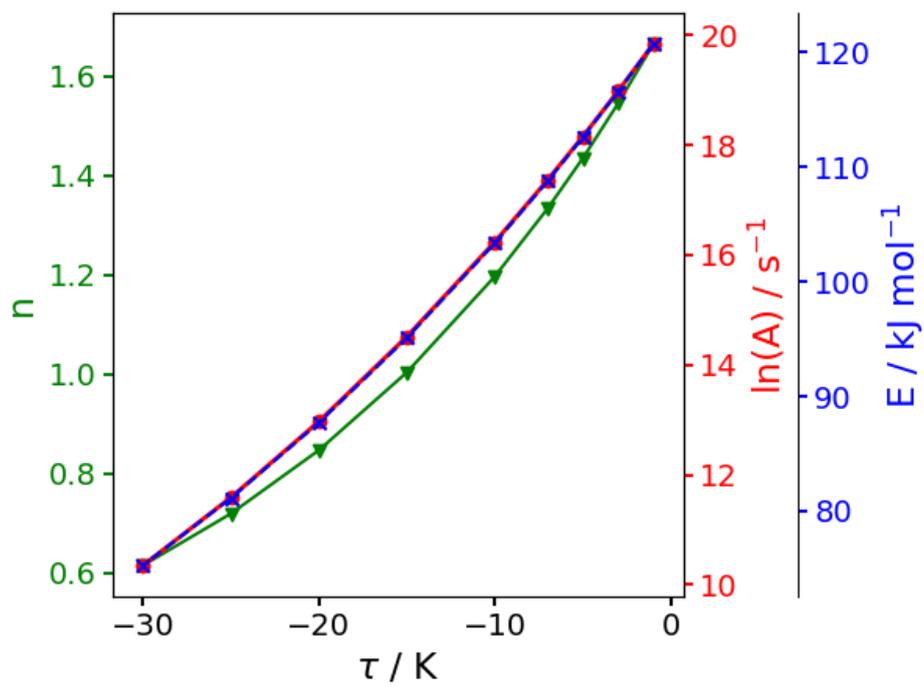


Figure 5: Corresponding values for the kinetic parameters of an n th-order Arrhenius model from the EGH model, for a heating rate of 20 K min^{-1} , $T_p = 600 \text{ K}$ and $\sigma = 30 \text{ K}$, with different values of τ .

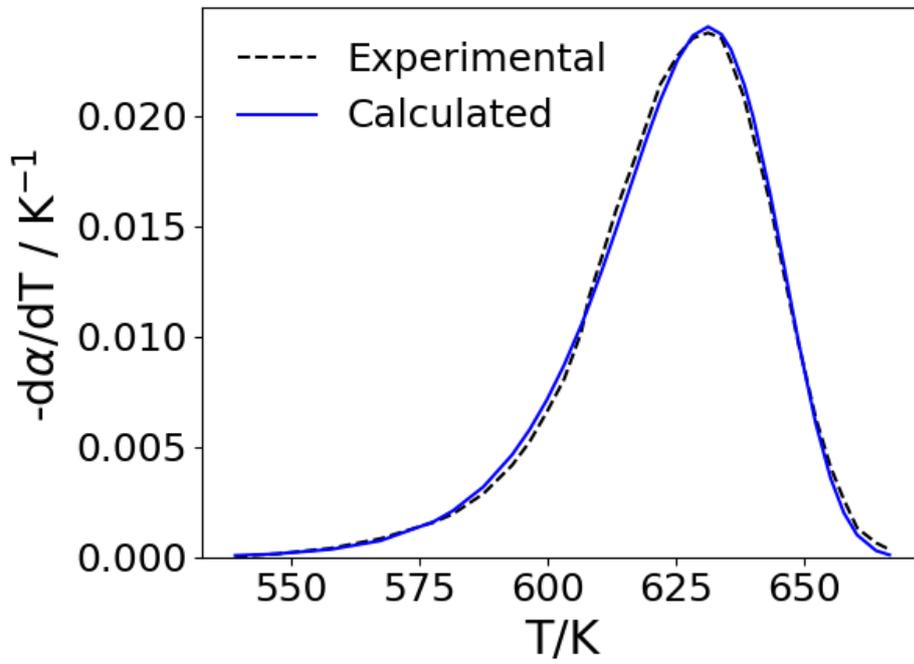


Figure 6: Calculated and experimental DTG curve of cellulose pyrolysis at 10 K min^{-1} [34].

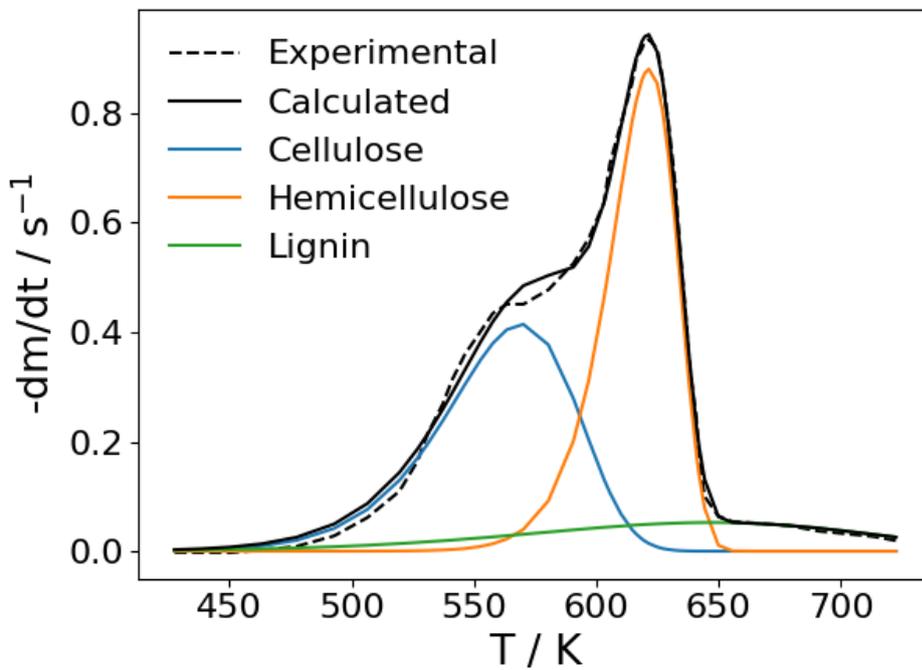
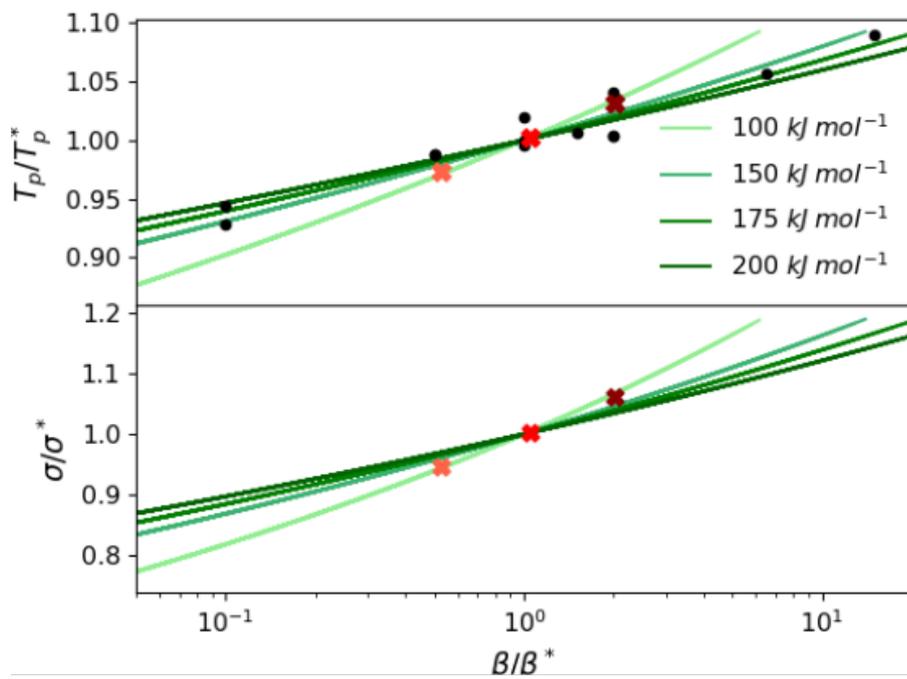
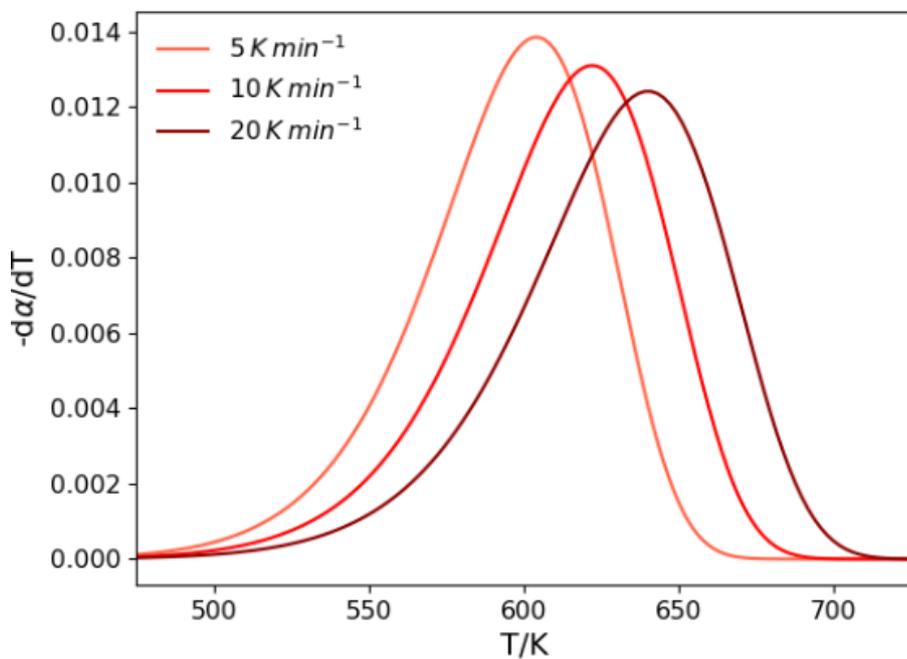


Figure 7: Deconvolution of experimental data of beech wood pyrolysis at 5 K min^{-1} [15].



(a)



(b)

Figure 8: (a) Different activation energy curves for cellulose, where the black dots are experimental data of peak temperature versus heating rate [34, 46, 47, 48, 49, 19, 21, 20, 50], and the red crosses are calculated points from b. (b) Calculated DTG curves for cellulose, derived for $E=100$ kJ/mol .

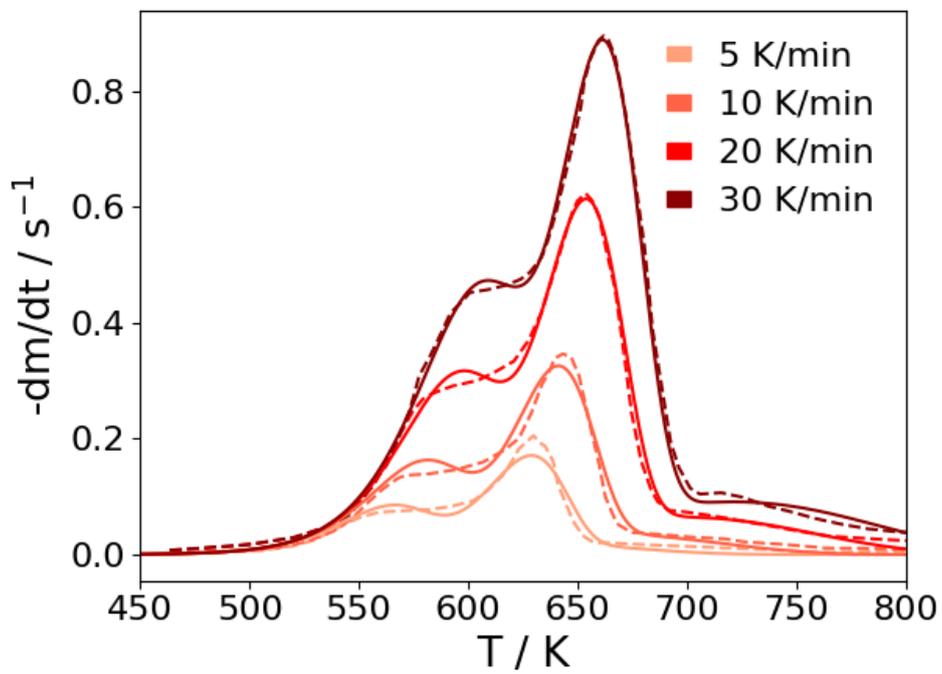


Figure 9: Simultaneous evaluation of experimental data from macadamia nut shell pyrolysis at different heating rates [45]; dashed line: experimental, solid line: calculated.