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1 Improved relationships between kinetic parameters

2 associated with biomass pyrolysis or combustion

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7

8 Abstract

- 9 Improved relationships between the kinetic parameters (pre-exponential factor and kinetic
- 10 energy) associated with biomass pyrolysis or combustion processes are proposed. These
- 11 relationships rely on observations of the mass and mass rate curves and on the experimental
- 12 data through computations performed on the kinetic model which describes the mass
- 13 evolution of each pseudo-component of the biomass during its thermal degradation. These
- 14 relationships improve the so-called kinetic compensation effect. They are here implemented
- as part of the Extended Independent Parallel Reaction (EIPR) model.

16

- 17 Keywords: Kinetic modeling; Optimal kinetic parameters; Kinetic compensation effect;
- 18 Biomass thermal degradation; EIPR model

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20 **1. Introduction**

21 Many papers have already been published which deal with the kinetic modeling of biomass 22 pyrolysis or combustion under low temperature ramps. Different methods or models are 23 available to simulate the thermal degradation of a material.

24 Differential or integral isoconversional methods are presented in (Vyazovkin et al., 2011).

25 They start from the single first-order differential equation which describes the evolution of

the sample extent of conversion with respect to time. Such methods do not solve this

27 differential equation. The Extended Independent Parallel Reaction (EIPR) model assumes the

28 presence of pseudo-components or constituents of the biomass submitted to thermal

29 degradation, for example hemicellulose, cellulose, lignin and char. These constituents are

30 supposed to decompose in an almost independent way, (Amutio et al., 2012; Babu, 2008;

31 Collard and Blin, 2014; Dhyani and Bhaskar, 2018). Comparisons between the differential

32 and integral isoconversional methods and the EIPR method are indicated in Table 1.

33 Table 1.

Using the isoconversional methods is quite simple, as they do not require a software dedicated to the resolution of the underlying ordinary differential equation. Nevertheless, these isoconversional methods often fail to simulate the mass and mass rate curves in a satisfying way, especially when multiple processes occur during the thermal degradation of the material, see for example (Brillard et al., 2017) in the case the thermal degradation of cellulose and cotton samples.

The independence assumption of the EIPR model is certainly a rough simplification of the
complex processes which occur during the pyrolysis or combustion of a biomass.
Nevertheless, this assumption is evoked in (Vyazovkin et al., 2011) and is used in (Dhahak et

al., 2019) who applied Ranzi's scheme presented for example in (Debiagi et al., 2015) to
simulate the combustion of beech, fir and oak woods. The overall resolution process through
the EIPR model requires a dedicated software and simultaneously returns the simulated
mass and mass rate curves. Error measurements between the experimental and simulated
mass and mass rate curves returned from the resolution are used to validate the optimal
values of the kinetic parameters.

The Distributed Activation Energy Model (DAEM) may be used to simulate the thermal degradation of a biomass. It considers a single first-order differential equation for each constituent of a biomass, but with a continuous distribution of activation energies having a density f(E) which is usually taken as a Gaussian, Weibull or logistic function. The DAEM model is based on the conversion of the first-order differential equation of the kinetic model to an integral whose computation requires a software and numerical tools.

55 Solving the single ordinary differential equation or system of ordinary differential equations and determining the optimal sets of kinetic parameters through the EIPR or DAEM models 56 takes a quite long time if the number of experimental times and data is high (usually many 57 thousands). To reduce the number of experimental time points without decreasing the 58 quality of the simulation, a selection of them is usually done. Nevertheless, the number of 59 stages to be taken into account in the thermal degradation cannot be reduced and the 60 61 computational time also highly increases with this number of stages. Trying to establish 62 relationships between the kinetic parameters or laws predicting some kinetic parameters was the topic of different papers. Criado et al. suggested a power law function of the 63 temperature for the pre-exponential factor, (Criado et al., 2005). The kinetic compensation 64 65 effect expresses a relationship between the logarithm of the pre-exponential factor A and

the activation energy *Ea* through an affine relation whose model-free coefficients only
depend on the temperature rate, (Galwey, 2004; Vyazovkin et al., 2011).

68 The present study proposes improved relationships between the pre-exponential factor and 69 the activation energy associated with each constituent of a biomass submitted to pyrolysis or combustion. These relationships are deduced from observations of the experimental mass 70 71 and mass rate curves and from the experimental data, through quite easy computations 72 performed on the first-order differential equation or system of equations associated with the kinetic model. These relationships divide by two the number of kinetic parameters to be 73 74 determined in the kinetic model. For example, only the activation energy associated with 75 each constituent has to be determined, the pre-exponential factor being deduced from the corresponding relationship. These relationships generalize the so-called kinetic 76 77 compensation effect. In the present study, these relationships are implemented in four 78 examples concerning the pyrolysis or combustion of different biomass. The simulations are performed using the EIPR model. In each case, different error measurements and the 79 80 computational times are computed and compared when considering either the classical resolution or that involving the relationships. The error measurements prove that the 81 82 resolution through the EIPR model which involves the relationships leads to slightly better simulations of the mass and mass rate curves than that using the classical resolution and in a 83 lower computational time. The reduction of the computational time is further observed to 84 become highly significant when the number of constituents to be considered in the thermal 85 degradation process increases. Even if these relationships are here implemented within the 86 87 framework of the EIPR model, they can surely be used in other models, for example the 88 DAEM one.

89

90 **2. Materials and methods**

91

2.1. Materials and thermogravimetric experiments

92 The present study relies on pyrolysis experiments previously performed on pure cellulose and palm nut shell, or on combustion experiments also previously performed on cotton 93 residue and coffee husk. Cellulose is the main constituent of the biomass. It is a linear chain 94 95 of D-glucose molecules. Cotton contains approximately 98% of cellulose. The pyrolysis and 96 combustion processes of pure cellulose and of cotton samples were analyzed and simulated in (Brillard et al., 2017). Palm nut shells are by-products of palm oil production. They are 97 obtained after extraction of palm oil, grinding of the nut, and extraction of almonds from the 98 99 nuts. Palm nut shells were provided by a Cameroonian Joint Initiative Group. The coffee husk is the envelope of coffee beans. Coffee husks were collected from a Cameroonian coffee 100 101 peeling factory. The pyrolysis and combustion processes of palm nut shells and of coffee 102 husks were analyzed and simulated in (Vitoussia et al., 2019). 103 Different characterizations were performed on these materials: proximate and ultimate analyses and calorific values. Their results can be found in the above-indicated papers. 104 105 Thermogravimetric experiments were performed on these materials in a thermobalance TA 106 Q500 Texas Instruments from room temperature to 900 °C, under pure nitrogen or under 107 synthetic air and under different low temperature rates (5, 10, 15, and 20 °C/min). More 108 details concerning the thermogravimetric experiments can be found in the above-indicated papers. In the present study, only the thermal degradations under a temperature ramp of 5 109 110 °C/min are considered. However, thermal degradations under other temperature ramps can 111 be efficiently simulated with the tools of the present study.

112

132

113	2.2. Relationships between kinetic parameters
114	The improved relationships between kinetic parameters which are proposed in the present
115	study are established in four cases, starting from the simplest case and ending with the more
116	complex one:
117	• A pyrolysis process occurring in a single stage (pure cellulose).
118	• A pyrolysis process occurring in multiple stages (palm nut shell sample, whose mass
119	rate curve presents two peaks and a long tail).
120	• A combustion process (cotton sample) occurring in a single devolatilization stage,
121	which is simulated with the Avrami-Erofeev reaction function of order 4, followed by
122	the char combustion stage simulated with the first-order reaction function (Mampel).
123	• A combustion process occurring in multiple stages (coffee husk sample).
124	During a pyrolysis process applied to a biomass, volatiles (CO, CO_2 and organic compounds)
125	are being emitted mainly between 150 and 600 °C. At the end of the pyrolysis process, the
126	char structure and the ash are remaining. Considering the lignocellulosic representation of
127	biomass, cellulose is usually the main component of a biomass. Cellulose pyrolysis occurs in
128	two or three stages, the first one being the constitution of active cellulose. Then saccharides,
129	cellubiose, furanes and other molecules appear, according to the so-called Broido's models,
130	(Bradbury et al., 1979), (Richter and Rein, 2017). Hemicellulose is built in small chains of
131	sugar units (xylose, arabinose, mannose, galactose, rhamnose). Its pyrolysis occurs in two

spaces in the cell wall between cellulose and hemicellulose. It is composed of cross-linked

steps, (Huang et al., 2017), the authors here focusing on the primary step. Lignin fills the

134 phenolic precursors. Its pyrolysis occurs in two stages, (Raveendran, 1996). The reaction

processes of biomass pyrolysis are analyzed in (Wang et al., 2017), (Várhegyi et al., 1997).
Biomass pyrolysis is one route to the production of valuable by-products.

The combustion of cellulose was analyzed in (Shafizadeh and Bradbury, 1979) and compared 137 to its pyrolysis. Reaction mechanisms were here proposed. The biomass combustion may be 138 139 decomposed in different stages: moisture evaporation, pyrolysis with gas production, char combustion, and gas oxidation. The volatiles are usually emitted at slightly lower 140 141 temperatures and with higher rates during a combustion process than during a pyrolysis process. Then the char structure is being degraded. Ash are the only remaining elements at 142 the end of the combustion process. In (Jenkins et al., 1998), the authors present a single, 143 long, and incomplete equation which accounts for the biomass combustion and they give the 144 values of the fifteen involved coefficients for hybrid poplar and rice straw. The biomass 145 146 combustion essentially leads to energy and heat production.

147 **2.2.1.** Relationship between the kinetic parameters when simulating a pyrolysis

148

process occurring in a single stage with a general reaction function

When submitting a pure cellulose sample to pyrolysis, a unique devolatilization peak is
observed, see (Brillard et al., 2017) and also the solid line curve of Fig. 1 b), section 3.1.1. In
some cases corresponding to intense pyrolysis processes like that of pure cellulose, an
Avrami-Erofeev reaction function may be chosen among the many available ones described
in (Vyazovkin et al., 2011) for example, to well simulate the pyrolysis process. In such case,
the kinetic model is usually written in terms of the extent of conversion given at time *t* as:

155
$$\alpha(t) = \frac{m_{ini} - m_s(t)}{m_{ini} - m_{fin}} \leftrightarrow m_s(t) = m_{ini} - \alpha(t) (m_{ini} - m_{fin}), \qquad (1)$$

156 as the first-order differential equation:

157
$$\alpha'(t) = k(T(t))f(\alpha(t)). \quad (2)$$

158 Differentiating this equation (2) with respect to time leads to:

159
$$\alpha''(t) = \frac{EaT'(t)}{RT^2(t)}k(T(t))f(\alpha(t)) + (k(T(t)))^2f'(\alpha(t))f(\alpha(t))$$

160
$$= k \left(T(t) \right) f \left(\alpha(t) \right) \left(\frac{EaT'(t)}{RT^2(t)} + k \left(T(t) \right) f' \left(\alpha(t) \right) \right).$$
(3)

From the definition (1) of the extent of conversion, the derivative of the mass sample is expressed as: $m'_s(t) = -\alpha'(t)(m_{ini} - m_{fin})$, whence the second derivative of the sample mass is expressed as: $m''_s(t) = -\alpha''(t)(m_{ini} - m_{fin})$. The opposite of the sample mass rate reaches a maximum at t^* , which implies that the second-order derivative of the extent of conversion is equal to 0 at t^* . This leads to the relationship between the two kinetic parameters A and Ea expressed as:

167
$$\frac{EaT'(t^*)}{RT^2(t^*)} + k(T(t^*))f'(\alpha(t^*)) = 0 \leftrightarrow A = -\frac{EaT'(t^*)}{RT^2(t^*)}exp\left(\frac{Ea}{RT(t^*)}\right)\frac{1}{f'(\alpha(t^*))}.$$
 (4)

This relationship (4) involves the temperature $T(t^*)$ at t^* , the temperature rate $T'(t^*)$ and also the extent of conversion $\alpha(t^*)$ at t^* . The time t^* at which the opposite of the mass rate takes its maximum has to be found in the experimental data, together with the temperature $T(t^*)$. The extent of conversion $\alpha(t^*)$ at this time t^* has also to be found or computed through its definition (1) from the experimental data.

173 In the case where the reaction function is the first-order one (Mampel), the computations 174 leading to the improved relationship between the kinetic parameters can be performed on 175 the kinetic model which considers the evolution of the mass of volatiles m_{vol} instead of the 176 extent of conversion (not shown here). The relationship (4) is slightly more complex than the kinetic compensation effect indicated in (Vyazovkin et al., 2011) and expressed as: $\ln(A) = aEa + b$, for model-free parameters aand b which depend on the heating rate. This relationship was used by many authors (Czajka et al., 2016; Ojha et al., 2017), for example, and also when applying the DAEM model (Huang et al., 2017; Xu et al., 2018), for example.

182 2.2.2. Relationship between the kinetic parameters when simulating a pyrolysis 183 process occurring in multiple stages

184 The pyrolysis of palm nut shell presents multiple stages, see (Vitoussia et al., 2019) and also the solid line curves of Fig. 2, section 3.1.2. In this case, the mass rate curve of Fig. 2 b) 185 presents a first small peak before 150 °C which corresponds to the moisture evaporation 186 stage. This stage will not be considered in the simulations. Then two thin peaks appear 187 between 250 and 350 °C. Between these two peaks, the mass rate does not go down to 0 188 189 %/s. On the right-hand side of the second peak, a long tail appears until 750-800 °C. 190 On the mass curve of Fig. 2 a), a first small decrease appears before 150 °C. Then a high decrease occurs between 250 and 350°C with a change of slope. Above 350 °C, the mass 191

192 goes on decreasing until 750-800 °C.

These changes of slope or peaks and tail may be explained by the presence of different
constituents which are being devolatilized in different but possibly superimposing
temperature ranges. Omitting the moisture evaporation stage, four constituents will be
considered in the EIPR model which will be applied to simulate this pyrolysis process.
Besides the hemicellulose and cellulose constituents of a lignocellulosic material, lignin
usually decomposes in two stages, (Jiang et al., 2018; Kawamoto, 2017).

In this pyrolysis case, the EIPR model consists in a set of ordinary differential equations. Each
first-order ordinary differential equation is written as:

201
$$\frac{dm_{vol,i}^{e}}{dt}(t) = k_{i}(T(t))f(m_{i}(0) - m_{vol,i}^{e}(t)), i = 1, ..., I, \quad (5)$$

where $m_{vol,i}^{e}(t)$ (kg) is the mass of volatiles emitted from the constituent *i* of the sample (*i*=1,...,*l*) and $m_i(0)$ (kg) is the initial mass of the constituent *i*. The kinetic constant $k_i(T)$ obeys an Arrhenius law: $k_i(T) = A_i \exp(-Ea_i/RT)$, where A_i (1/s) (resp. Ea_i (J/mol) is the pre-exponential factor (resp. the activation energy) associated with the constituent *i*. The initial value $m_{vol,i}^{e}(0)$ of volatiles emitted from the constituent *i* is equal to 0 kg. For each constituent, the relationship (4) can be used which give the value of the preexponential factor A_i in terms of the activation energy Ea_i and of the time t_i^* at which the

209 mass of volatiles emitted from the constituent i is maximal, according to:

210
$$A_{i} = -\frac{Ea_{i}T'(t_{i}^{*})}{RT^{2}(t_{i}^{*})}exp\left(\frac{Ea_{i}}{RT(t_{i}^{*})}\right)\frac{1}{f'\left(\alpha(t_{i}^{*})\right)}.$$
 (6)

In each relationship (6), the time t_i^* at which the mass rate of volatiles emitted from the constituent *i* is maximal has to be determined first observing the experimental mass rate curve and analyzing the experimental data. This is easy in the case of a well identified peak. In the cases of a tail or of a shoulder, the determination of this time t_i^* is more complicated.

215 2.2.3. Relationship between the kinetic parameters when simulating a combustion 216 process with a single devolatilization stage

The combustion of a cotton sample was analyzed in (Brillard et al., 2017). A unique
devolatilization peak may be observed, which is followed by a unique char combustion peak,

see also the solid line curve of Fig. 3 b), section 3.2.1. Cotton is composed of cellulose up to 98%. This unique constituent contains a fraction τ_{vol} of volatiles to be emitted and the remaining fraction $1 - \tau_{vol}$ of char to be consumed in the final stage of the combustion process. Here the devolatilization stage occurs between 200 and 350 °C. The char combustion stage occurs between 350 and 470 °C. Above 470 °C, the mass rate is almost equal to 0 g/s and the mass is stable at 2.2×10^{-3} g, the remaining ash weight.

In this case, the kinetic system is written in terms of the extent of conversion α_{vol} defined

226 through
$$\alpha_{vol}(t) = m_{vol}(t) / \left(\tau_{vol} \left(m_{ini} - m_{fin} \right) \right)$$
 as:

227
$$\begin{cases} \alpha'_{vol}(t) = k_{vol}(T(t))f(\alpha_{vol}(t))\frac{1}{\tau_{vol}}\\ m'_{char}(t) = k_{comb}(T(t))\left(\frac{1-\tau_{vol}}{\tau_{vol}}m_{vol}(t) - m_{char}(t)\right)P_{0_2}, \end{cases}$$
(7)

228 Differentiating the first equation of (7) with respect to time leads to:

229
$$\alpha_{vol}^{\prime\prime}(t) = k_{vol} \left(T(t) \right) \frac{E a_{vol} T^{\prime}(t)}{R T(t)^2} f\left(\alpha_{vol}(t) \right) \frac{1}{\tau_{vol}}$$

230
$$+ k_{vol}(T(t))f'(\alpha_{vol}(t))k_{vol}(T(t))f(\alpha_{vol}(t))\frac{1}{(\tau_{vol})^2}.$$
 (8)

At the time t^* where the devolatilization peak reaches its maximum, this second derivative cancels. This leads to the relationship:

233
$$A_{vol} = -\frac{\tau_{vol}}{f'(\alpha_{vol}(t^*))} \frac{Ea_{vol}T'(t^*)}{RT^2(t^*)} exp\left(\frac{Ea_{vol}}{RT(t^*)}\right), \quad (9)$$

- which has the same structure as (4).
- 235 Differentiating the second equation of (7) with respect to time leads to:

236
$$m_{char}''(t) = k_{comb} (T(t)) \frac{Ea_{comb} T'(t)}{RT(t)^2} \left(\frac{1 - \tau_{vol}}{\tau_{vol}} m_{vol}(t) - m_{char}(t) \right) P_{O_2}$$

237
$$+ k_{comb} (T(t)) \left(\frac{1 - \tau_{vol}}{\tau_{vol}} m'_{vol}(t) - m'_{char}(t) \right) P_{O_2}$$

238
$$= k_{comb} \left(T(t)\right) \frac{Ea_{comb}T'(t)}{RT(t)^2} \left(\frac{1-\tau_{vol}}{\tau_{vol}} m_{vol}(t) - m_{char}(t)\right) P_{O_2}$$

239
$$+ k_{comb} \left(T(t) \right) \left(\frac{1 - \tau_{vol}}{\tau_{vol}} \left(m_{ini} - m_{fin} \right) k_{vol} \left(T(t) \right) f \left(\alpha_{vol}(t) \right) \right)$$

240
$$-k_{comb}(T(t))\left(\frac{1-\tau_{vol}}{\tau_{vol}}m_{vol}(t)-m_{char}(t)\right)P_{O_2}\right)P_{O_2}.$$
 (10)

At the time t^{**} where the second derivative $m''_{char}(t)$ is equal to 0, (10) becomes

242
$$0 = \left(\frac{Ea_{comb}T'(t^{**})}{RT(t^{**})^2} - k_{comb}(T(t^{**}))P_{O_2}\right) \left(\frac{1 - \tau_{vol}}{\tau_{vol}}m_{vol}(t^{**}) - m_{char}(t^{**})\right)$$

243
$$+ \frac{1 - \tau_{vol}}{\tau_{vol}} (m_{ini} - m_{fin}) k_{vol} (T(t^{**})) f(\alpha_{vol}(t^{**})). \quad (11)$$

244 Defining the terms:

245
$$\alpha = \frac{1 - \tau_{vol}}{\tau_{vol}} m_{vol}(t^{**}) - m_{char}(t^{**}), \quad (12)$$

246
$$\beta = \frac{1 - \tau_{vol}}{\tau_{vol}} (m_{ini} - m_{fin}) k_{vol} (T(t^{**})) f(\alpha_{vol}(t^{**})), \quad (13)$$

the equation (11) leads to the following relationship between A_{comb} and Ea_{comb} :

248
$$A_{comb} = \frac{1}{P_{O_2}} exp\left(\frac{Ea_{comb}}{RT(t^{**})}\right) \left(\frac{Ea_{comb}T'(t^{**})}{RT(t^{**})^2} + \frac{\beta}{\alpha}\right).$$
(14)

In the case where the reaction function associated with the devolatilization stage is the firstorder one (Mampel), the computations leading to the improved relationship between the

kinetic parameters can again be performed on the kinetic model whose first equation considers the evolution of the mass of volatiles m_{vol} instead of the extent of conversion (not shown here).

254

2.2.4. Relationship between the kinetic parameters in the case of a combustion

255 process whose devolatilization occurs in multiple stages

The combustion of a coffee husk sample occurs in multiple stages, (Vitoussia et al., 2019), see also the solid line curves of Fig. 4, section 3.2.2. The mass rate curve (solid line curve of Fig. 4 b)) presents a first peak which ends before 150 °C and which corresponds to the moisture evaporation. A second peak which occurs between 150 and 350 °C and with shoulders on its both sides and which corresponds to the devolatilization of the sample. Finally, a third peak which occurs between 350 and 480 °C and which corresponds to the char combustion.

As in the preceding simulations, the moisture evaporation stage will not be considered in the present study, although the mass loss is here relatively important. Five stages may be considered respectively corresponding to the two peaks, the shoulders on both sides of the first peak and the important degradation of a constituent of the material around 370 °C. Notice that in the present situation, the char combustion peak has almost the same size as the devolatilization peak.

In this combustion case, the relationships between the kinetic parameters associated with
the devolatilization stages through (9) are used to divide by two the number of unknown
parameters. The relationship (14) is used for the simulation of the char combustion.

272

273 **2.2.5.** Simulations through the EIPR model and error measurements

In the present study, the Extended Independent Parallel Reaction model is used to simulate the thermal degradations of the different samples under consideration. The first reason is that this model preserves the differential equation or system which describes the evolution of the devolatilization or of the char combustion with respect to time. The second reason is that solving the EIPR model directly returns simulations of the mass and mass rate curves, together with error measurements and computational time.

The EIPR model consists to solve the kinetic equation or system (2), (5), or (7), depending on the thermal degradation process, first with initial guesses of the kinetic parameters. In the present simulations, these initial guesses of the kinetic parameters are chosen not too far and not too close from the final values. The routine 'ode' of the Scilab software (version 6.0.2) is here used. The optimal values of the kinetic parameters are obtained minimizing the objective function chosen as:

286
$$\sum_{j=1}^{N} \left(\left(\frac{dm_{vol,i}^{e}}{dt} \right)_{exp} (t_j) \left(\left(\frac{dm_{vol,i}^{e}}{dt} \right)_{exp} (t_j) - \left(\frac{dm_{vol,i}^{e}}{dt} \right)_{sim} (t_j) \right)^2 \right)^2, \quad (15)$$

through the routine 'datafit' of Scilab. This objective function indeed led to a unique
minimizer in a neighborhood of the optimal set of kinetic parameters, (Brillard and Brilhac,
2020). In (15), N is the overall number of experimental time points. The equations or
systems (2), (5), or (7) are finally solved with the optimal values again using the routine
'ode' and the code returns the simulated mass and mass rate curves.
To validate these simulations, different error measurements are considered:

293 - the maximal difference between the experimental and simulated mass rate curves,

294 hereafter denoted as l_{∞} (kg/s),

295 - the square root of the squared difference between the experimental and simulated 296 mass rate curves, hereafter denoted as l_2 (kg/s),

297 - R^2 determination coefficients for the mass R_m^2 , mass rate R_{mr}^2 and overall R_o^2

- variations. These determination coefficients should be as close to 1 as possible tovalidate the simulations.
- The precise expressions of these error measurements can be found for example in (Brillardet al., 2021).
- 302 The computations associated with the five cases evoked in subsection 2.2 are performed
- 303 using the classical (without the relationships between pre-exponential factor and activation
- 304 energy) and improved (taking into account the relationships between the kinetic
- 305 parameters) EIPR models on a DELL Latitude 5400 laptop through the free Scilab software
- 306 version 6.0.2 and some of its routines. Every software able to read experimental data as
- 307 returned by the thermobalance, to solve a differential equation and to minimize an objective
- 308 function associating the experimental and simulated data with respect to the kinetic
- 309 parameters to be determined can be used with success.
- 310
- 311 3. Results and discussion
- 312 **3.1. Simulations of pyrolysis processes**
- 313 **3.1.1.** Simulation of a pyrolysis process occurring in a single stage a second-order
- 314 Avrami-Erofeev reaction function (cellulose sample)
- 315 The sample containing a single component (cellulose), the mass rate curve presents a simple
- shape with a unique devolatilization peak, see Fig. 1 b) below. Because this unique
- 317 devolatilization peak occurs between 200 and 300 °C, the simulations are performed in the

318 temperature range 150-450 °C. An Avrami-Erofeev function of order 2 defined in terms of 319 the extent of conversion α through:

320
$$f_2(\alpha) = 2(1-\alpha)(-\log(1-\alpha))^{0.25}$$
, (16)

is used. 5221 experimental times are considered. According to Fig. 1 b) and to the experimental data, the temperature at which the maximal mass rate is reached is equal to 336.19 °C and the corresponding time t^* is equal to 106.8 s.

Nevertheless, choosing the temperature $T(t^*)$ at which the maximal mass rate is reached

equal to 336.19 °C and the corresponding time t^* equal to 106.8 s leads to not totally

326 satisfying simulations (not shown here) when applying the improved EIPR model. Choosing

instead the temperature $T(t^*)$ at which the maximal mass rate is reached equal to 339.75 °C

328 (+3.56 °C) and the corresponding time t^* equal to 107.6 s (+0.8 s) leads to better simulation

results, see Fig. 1. Table 2 gathers the initial and optimal values of the kinetic parameters

determined through the classical and improved EIPR models, the different error

331 measurements and the computational times.

332 Table 2.

333 The optimal values of the kinetic parameters differ, being slightly greater for the improved

model than for the classical one. The error measurements are slightly better for the

- improved model than for the classical one. The computational time for this improved EIPR
- model is lower than that of the classical one.

The simulations with the classical and improved EIPR models are gathered in Fig. 1.

338 Figure 1.

It is difficult to identify the simulated mass and mass rate curves as they quite perfectly
superimpose. The simulated mass curves are below the experimental one and the simulated
mass rate curve start a little bit earlier and they go back to 0 a little bit earlier than the
experimental one. The maximal mass rate of the improved EIPR model is reached at 339.29
°C, while that of the classical EIPR model is reached at 338.85 °C.

344 **3.1.2.** Simulations of a pyrolysis process with multiple stages (palm nut shell sample)

345 The pyrolysis process of a palm nut shell under nitrogen and a temperature ramp of 5 °C/min 346 occurs in four stages, see the solid line curves of Fig. 2 below. This presence of four stages is 347 the consequence of three components (hemicellulose, cellulose and lignin) in the biomass which decompose in different but possibly superimposing temperature ranges. The fractions 348 349 of these three components were determined in (Vitoussia et al., 2019) applying Van Soest's protocol. The chosen fractions of the initial mass of the four constituents are taken equal to: 350 351 0.27, 0.30, 0.24 and 0.19, as estimated from the relative importance of the peaks or tail of Fig. 2 b). 352

For the improved model, the temperatures $T(t^*)$ which correspond to the maximal

devolatilization of each constituent are determined equal to: 270.5, 342.1, 319.0, and 362.2

³⁵⁵ °C, respectively, corresponding to the times 5708, 6567, 6290, and 6809 s. 12588

experimental times and data are used corresponding to temperatures between 150 and 850°C.

The initial guesses and the optimal values of the kinetic parameters are gathered in Table 3, together with the error measurements and the computational times.

360 Table 3.

The optimal values of the activation energies are almost the same for both models and they do not differ so much from the initial values. The optimal values of the pre-exponential factors slightly differ. The error measurements are slightly better with the improved EIPR model when compared to that of the classical one. The computational time with the classical model is approximately equal to five times that with the improved model. Taking into account the relationships (6) in the simulations with the EIPR model significantly reduces the computational time and increases the quality of these simulations.

368 The experimental and simulated mass and mass rate curves are gathered in Fig. 2.

369 Figure 2.

The simulated mass curve are both slightly below the experimental one. The simulated mass rate curves start a little bit too early. Nevertheless, the determination coefficients are sufficiently high to accept the simulations, with slightly higher values for the improved model.

374

3.2. Simulation of combustion processes

375 3.2.1. Simulation of a combustion process with a single devolatilization stage

As already indicated, cotton is composed of cellulose up to 98%. A unique and very thin devolatilization peak appears in the mass rate curve which is followed by a small char combustion peak, see the solid line curve of Fig. 3 b).

To simulate in an appropriate way the thinness of the devolatilization peak, an Avrami-Erofeev or order 4 is used which is given as:

381
$$f_4(\alpha) = 4(1-\alpha)(-\log(1-\alpha))^{0.75}$$
. (17)

382 1033 experimental times are used between room temperature and 900 °C. The proportion τ_{vol} of volatiles is taken equal to 0.86, whence that of char τ_{char} is equal to 0.14. The time t^* 383 at which the maximal devolatilization rate is reached is taken equal to 4150 s, corresponding 384 to a temperature equal to 323.01 °C. This temperature $T(t^*)$ is slightly smaller than the 385 temperature (339.75 °C) at which the devolatilization peak reached its maximum during the 386 387 pyrolysis process of the pure cellulose sample. The maximal height of this devolatilization peak is equal to 0.24 in the pyrolysis case and to 0.33 in the combustion case. Oxygen is 388 known to enhance the degradation process. The time t^{**} at which the maximal char 389 combustion rate was reached is taken equal to 5550 s, corresponding to a temperature 390 equal to 439.59 °C. 391 392 According to the procedure described in subsection 2.2.3, the initial and optimal values of 393 the kinetic parameters are gathered in Table 4, together with the error measurements and 394 the computational times for the classical and improved EIPR models. 395 Table 4. 396 With the improved EIPR model, the kinetic parameters are significantly changed. The error 397 measurements are very slightly worse, but the computational time is divided by more than 2. 398 399 The experimental and simulated mass and mass rate curves are gathered in Fig. 3. 400 Figure 3. 401 It is difficult to identify the two simulated mass curves as they do well superimpose. For the 402 mass rate curves, that with the improved EIPR model presents a char combustion peak slightly higher than the experimental one. This is coherent with the values of the kinetic 403

parameters presented in Table 4. Part of these very slightly worse error measurements and
slightly too high simulated char combustion peak may be explained by the absence of a
further constituent in the cotton sample (apart from cellulose). The mass rate curve does not
go down to 0 between the devolatilization and char combustion peaks, possibly due to the
presence of a further constituent in the cotton sample.

- 3.2.2. Simulation of a combustion process whose devolatilization occurs in multiple
 stages
- 411 Five constituents, plus the char, were considered for the devolatilization of the coffee husk
- sample. Their respective fractions are chosen equal to: 0.08, 0.40, 0.06, 0.26, and 0.20. The
- 413 proportions of volatiles in each constituent were respectively chosen equal to: 0.60, 0.58,
- 414 0.65, 0.55, and 0.53. Mampel's reaction function is here used for the devolatilization of the

415 five constituents. 11998 experimental times and data are considered.

416 The initial and optimal values of the kinetic parameters returned by the classical and

417 improved EIPR models are gathered in Table 5.

418 Table 5.

419 With the improved EIPR model, the pre-exponential factors are significantly changed, the

420 error measurements are slightly better than that of the classical model and the

421 computational time is divided by more than 7. The kinetic model involves six pairs of kinetic

422 parameters and the EIPR model involving the relationships between the kinetic parameters

423 is especially efficient in this case.

424 The experimental and simulated mass and mass rate curves are gathered in Fig. 4.

425 Figure 4.

The simulated mass and mass rate curves returned by both models are quite well superimposed. However, the error measurements are slightly better when applying the improved EIPR model and the computational time is much smaller.

429

430 **4.** Conclusion

Improved relationships were established between the pre-exponential factor and the 431 432 activation energy associated with each constituent of a biomass submitted to pyrolysis or 433 combustion under low temperature ramps. They only involve experimental data through 434 easy computations on the equations of the underlying model. Simulations performed using the EIPR model for different biomass proved that the error measurements between the 435 experimental and simulated mass and mass rate curves are slightly improved using these 436 437 relationships. The computational time is here significantly reduced, especially in the cases 438 where multiple constituents are taken into account in the kinetic model.

439

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444

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447

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494

535 Figure Captions

- 536 Fig. 1. Experimental (solid line) and simulated through the classical (dotted line) and
- 537 improved (hyphened line) mass a) and mass rate b) curves for the pyrolysis of cellulose
- 538 under nitrogen and a temperature ramp of 5 °C/min. The Avrami-Erofeev reaction function
- 539 of order 2 is here used.
- 540 Fig. 2. Experimental (solid line), simulated with the classical (dotted line) or improved (large
- 541 hyphened line) EIPR model mass a) and mass rate b) curves for the pyrolysis of a palm nut
- shell under nitrogen and a temperature rate of 5 °C/min.
- Fig. 3. Experimental (solid line), simulated with the classical (dotted line) or improved (large
 hyphened line) EIPR model mass a) and mass rate b) curves for the combustion of a cotton
 sample under air and a temperature rate of 5 °C/min.
- 546 Fig. 4. Experimental (solid line), simulated with the classical (dotted line) or improved (large
- 547 hyphened line) EIPR model mass a) and mass rate b) curves for the combustion of a coffee
- 548 husk sample under air and a temperature rate of 5 °C/min.

Table 1. Process diagram of the isoconversional methods and of the Extended Independent Parallel Reaction (EIPR) Method.

	Isoconversional Methods	EIPR model
	A unique equation (2) which describes the evolution with	A single first-order differential equation describes the
	respect to time of the extent of conversion α .	evolution with respect to time of the mass of volatiles
	The case of independent and parallel reactions is evoked in	being emitted from each constituent and/or of the
	(Vyazovkin et al., 2011) for the thermal degradation of	fraction of the char from each constituent which is burnt.
Kinetic equation	biomass and fossil fuels, which leads to a linear combination of equations (2).	The number of equations depends on the thermal degradation process (pyrolysis or combustion) and on the number of stages as observed in the experimental mass and mass rate curves. The fractions of these constituents in the raw material are also estimated from these observations
Parameters to be determined	A unique set of pre-exponential factor and activation energy. These kinetic parameters are indeed global for the material, but they depend on the extent of conversion α , whence on time.	A single set of kinetic parameters is associated with each constituent. As many pairs of pre-exponential factors and activation energies have to be determined as the number of constituents to be considered in the EIPR model. These sets of kinetic parameters are global in time.

Differential isoconversional method:

Consider (at least) three temperature ramps. Apply the logarithm to equation (2) for each temperature ramp and change the variable:

$$\ln\left(T_i'(t)\left(\frac{d\alpha}{dT}\right)_{\alpha,i}\right) = \ln\left(A_\alpha f(\alpha)\right) - \frac{Ea_\alpha}{RT_{\alpha,i}}$$

Plot the left-hand side member in terms of 1/T. Apply a linear regression method.

Integral isoconversional methods:

Integrate equation (12) and change the variable:

$$g(\alpha) = \int_0^\alpha \frac{d\alpha}{f(\alpha)} = A \int_0^t \exp\left(-\frac{Ea}{RT}\right) dt$$
$$= \frac{A}{T'(t)} \int_0^T \exp\left(-\frac{Ea}{RT}\right) dT$$

Introduce approximations of the right-hand side member, leading to Flynn-Ozawa-Wall, Kissinger-Akahira-Sunose... methods, (Vyazovkin et al., 2011).

Consider (at least) three temperature ramps.

Apply a logarithm.

Plot the left-hand side member in terms of 1/T. Apply a linear regression method. Solve the equation or system of equations of the model with a dedicated software and minimize a chosen objective function which gathers the experimental and simulated masses and mass rates, to determine the optimal values of the pair(s) of kinetic parameters.

Process

- **Table 2**. Initial and optimal values of the pre-exponential factor *A* and of the activation
- energy *Ea* determined through the classical and improved EIPR models with an Avrami-
- 554 Erofeev reaction of order 2, for the cellulose pyrolysis. Error measurements and
- 555 computational time.

	Classical		Improved	
	Initial value	Optimal value	Initial value	Optimal value
A (1/s)	9.00×10 ¹³	9.00×10 ¹³		9.96×10 ¹³
<i>Ea</i> (kJ/mol)	190000.0	192318.6	190000.0	192968.3
l_{∞} (%/s)		0.0226		0.0200
l ₂ (%/s)		0.5106		0.4761
R_{m}^{2} (-)		0.998		0.999
R_{mr}^2 (-)		0.985		0.988
R_{o}^{2} (-)		0.983		0.988
Computational time (s)		37.7		28.6

556

- **Table 3**. Optimal values of the pre-exponential factors and of the activation energies
- determined through the classical and improved EIPR models, for the pyrolysis of palm nut
- 560 shells. Error measurements and computational time (s).

	Classical		Improved	
	Initial value	Optimal value	Initial	Optimal
			value	value
A ₁ (1/s)	9.60×10 ⁸	9.60×10 ⁸		1.10×10 ⁹
Ea_1 (kJ/mol)	119000.0	119000.0	119000.0	119000.0
A ₂ (1/s)	5.0×10 ⁷	5.0×10 ⁷		3.3×10 ⁷
Ea_2 (kJ/mol)	118000.0	118000.0	120000.0	118000.0
A ₃ (1/s)	7300.0	7300.0		8869.0
Ea_3 (kJ/mol)	75000.0	75000.0	75000.0	75000.0
A ₄ (1/s)	0.20	0.10		0.22
Ea_4 (kJ/mol)	30000.0	30000.0	30000.0	30000.0
l_{∞} (%/s)		0.0240		0.0204
l ₂ (%/s)		0.5235		0.3638
R_{m}^{2} (-)		0.994		0.983
R_{mr}^2 (-)		0.905		0.954
R_{o}^{2} (-)		0.899		0.937
Computational time (s)		2117.8		442.3

561

- **Table 4**. Initial and optimal values of the pre-exponential factor *A* and of the activation
- sea energy *Ea* determined through the classical and improved EIPR models, for the combustion

	Classical		Improved	
	Initial value	Optimal value	Initial value	Optimal value
A_{vol} (1/s)	20000.0	19906.9		6682.0
<i>Ea_{vol}</i> (kJ/mol)	79000.0	79455.6	79000.0	74361.8
A _{comb} (1/(s.Pa))	7.40×10 ⁸	7.40×10 ⁸		6.63×10 ¹⁸
Ea _{comb} (kJ/mol)	212000.0	212000.0	212000.0	345343.1
l_{∞} (%/s)		0.0698		0.0745
l ₂ (%/s)		0.3051		0.3180
R_m^2 (-)		0.998		0.998
R_{mr}^2 (-)		0.931		0.926
R_{o}^{2} (-)		0.929		0.924
Computational time (s)		70.2		32.6

of a cotton sample. Error measurements and computational time.

566

- **Table 5**. Initial and optimal values of the pre-exponential factor *A* and of the activation
- senergy *Ea* determined through the classical and improved EIPR models, for the combustion

	Classical		Improved	
	Initial value	Optimal value	Initial value	Optimal value
A _{vol,1} (1/s)	6.60×10 ⁸	7.17×10 ⁸		5.69×10 ⁸
$Ea_{vol,1}$ (kJ/mol)	107000.0	107000.0	107000.0	107000.0
$A_{vol,2}$ (1/s)	6.50×10 ⁷	7.18×10 ⁷		8.35×10 ⁷
$Ea_{vol,2}$ (kJ/mol)	112800.0	112800.0	112800.0	112800.0
$A_{vol,3}$ (1/s)	6.50×10 ⁷	6.50×10 ⁷		1.29×10 ⁸
$Ea_{vol,3}$ (kJ/mol)	121000.0	121000.0	121000.0	121000.0
$A_{vol.4}$ (1/s)	100000.0	100043.7		116640.2
$Ea_{vol.4}$ (kJ/mol)	89000.0	89000.0	89000.0	89000.0
$A_{vol.5}$ (1/s)	1000.0	1000.4		1722.5
$Ea_{vol.5}$ (kJ/mol)	75000.0	75000.0	75000.0	75000.0
A_{comb} (1/(s.Pa))	150000.0	157826.5		149843.7
Ea _{comb} (kJ/mol)	165000.0	165000.0	165000.0	165000.0
l_{∞} (%/s)		0.0107		0.0108
l ₂ (%/s)		0.2874		0.2313
R_{m}^{2} (-)		0.998		1.000
R_{mr}^2 (-)		0.974		0.983
R_{o}^{2} (-)		0.971		0.982
Computational time (s)		5605.5		740.5

570 of coffee husks. Error measurements and computational time.

571













a)

b)

576 **Fig. 2**.





b)

Fig. 3.



a)

b)

580 **Fig. 4**.