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Functional Weibull-based models of steel fracture toughness for structural risk analysis: estimation and selection

Nadia Pérot^a, Nicolas Bousquet^b

Summary: A key input component of numerous reliability studies of industrial components or structures, steel fracture toughness is usually considered as a random process because of its natural variability. Moreover, toughness presents a high sensitivity to temperature which also plays a fundamental role, as an environmental forcing, in such studies. Therefore a particular attention has to be paid to the assessment of its stochastic functional modelling, by means of a statistical analysis of indirect measures that suffer from heterogeneity and censoring. While a Weibull shape arising from statistical physics is recognized as the most relevant approach to represent local variability, the selection of best functional parameters (function of temperature) requires an accurate estimation and testing methodology. Its development is motivated by several limitations of the common statistical practices in the field of fracture toughness, which are related to data treatment and model selection. Illustrated by the exploration of a database feed by several European manufacturers or exploiters, this article establishes the main steps of such a methodology, implemented in a dedicated software tool.

Keywords: Weibull, Master Curve, Censoring, Genetic algorithm, Thickness correction, Model selection, fracture toughness, reliability

1. INTRODUCTION

1 Structural risk analysis (SRA) plays a key role in the management of passive and costly
2 industrial components, especially those belonging to power production vessels or other
3 pressurized systems for which safety must be guaranteed in critical situations. Such situations
4 typically occur when a corrective action is performed that results in high-level stresses for
5 the structure. For instance, Pressurized Water Reactor vessels must be cooled down by
6 safety injections while still under pressure ; the injection of cold water causes a thermal
7 shock transient which can weaken the integrity of the component [13]. SRA methodologies
8 are mostly based on the simulation of degradation processes that have not been observed in
9 reality or can not be reproduced in laboratory [25]. Roughly speaking, simulation models put
10 *loads* L (including controllable actions) into competition with *capacities* R , and situations
11 for which $L \geq R$ are defined as failures [14].

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12 Amongst capacities the case of material fracture toughness is of major interest, since
13 this property traduces the capability of the material to resist to pre-initiated crack
14 propagation [19]. According to the weakest link (WL) physical theory [18], pre-initiated
15 cracks correspond to heterogeneities within the crystal lattice of the material, and often
16 arises from manufacturing defects. Such heterogeneities appear randomly, which is traduced
17 by a natural variability of the fracture toughness (see Figure 1 for an illustration) and
18 its modelling as a random variable in the dedicated literature [32]. Consequently, $L - R$
19 is randomized and a crucial reliability indicator is the probability $P(L > R)$ of a failure
20 event. Numerous SRA methods deal with the computation of this probability, based on
21 numerical exploration of the simulation model [34]. Steel being one of the most used
22 materials in industry, the high sensitivity of its fracture toughness to temperature variations
23 is representative of the statistical modelling difficulties encountered by reliability engineers
24 [11]. Predicting how the toughness increases with temperature, from a brittle to a ductile
25 nature, and summarizing this transition by a representative temperature [6], are two key
26 issues of detailed SRA studies [38].

27
28 [Figure 1 about here.]

29 According to the WL theory, the brittle fracture toughness K_{IC} is explained at low
30 temperature T by a functional Weibull model, popularized by [42] for a wide range of
31 ferritic steels, and established as a US norm [2] under the so-called *Master Curve* (MC)
32 denomination:

$$P(K_{IC}(T) < x) = 1 - \exp \left\{ - \left(\frac{x - K_{\min}}{K_0(T) - K_{\min}} \right)^\alpha \right\} \quad (1)$$

33 with shape parameter $\alpha = 4$, location parameter (or *brittle stage*) $K_{\min} = 20 \text{ MPa}\cdot\text{m}^{1/2}$ and
34 with functional form

$$K_0(T) - K_{\min} = b_1 + b_2 \exp(-b_3 \cdot T). \quad (2)$$

35 The estimation of the parameter vector $\theta = (b_1, b_2, b_3) \in \mathbb{R}_*^+$ is conducted (usually using
36 maximum likelihood techniques [46]) from fracture toughness observations produced from
37 destructive tests on small-size specimen [7], that requires a so-called *thickness correction* to
38 homogenize the corresponding observations. However, in the common assessment practices
39 [23, 29, 37], several limitations of the MC model and methodological lacks interfere with
40 an accurate use of statistical modelling, especially about the prediction of the brittle stage
41 K_{\min} , which must be not overestimated as it resumes the minimal resistance to cold shocks.

- 42 1. The MC model and the value $\alpha = 4$ are relevant based on an assumption on the
43 plasticity of cracks priming [43] and chemical homogeneity, which are not fully ensured
44 in the case of welded components, and within all temperature ranges corresponding
45 to experimental conditions. Consequently, the MC model threatens to be too rigid to
46 explain the variability of observations, especially when the latter comes from various
47 experiments conducted on specimen of close material grades by different laboratories.
48 Despite several adaptations of methodologies of toughness quantification based on the

MC model (see for instance [47]), this lack of flexibility was still noticed by [22], from a modelling work guided by the EURO database originally used by [44], that aggregates steels from various European manufacturers. Alternatively, a recent competitor of the MC methodology, the Unified Curve method [27], offers a possible variation of the curve shape when the degree of embrittlement increases, but was criticized by [45] for its lack of universality. Adopting a universal encompassing approach, [22] provided a first answer to the issue of versatility by adding α to the vector θ of free parameters and proposing a statistical assessment based on maximum likelihood estimation (MLE). However, these authors missed the fact that adding this supplementary degree of freedom forbids to agglomerate heterogeneous observations directly using the specimen thickness correction proposed in the MC methodology, a key ingredient of the latter.

2. Experimental data, consisting in a transformation of priming measures on precracked test samples, present several degrees of validity fixed by norms [4, 20]. Especially, some of them correspond to limit (quasi-valid) cases when the level of energy used for the destructive test is too low or too high. Being currently rejected in the assessment methodologies of the MC model, these observations still yield relevant statistical censoring information, and should be used in the assessment of any toughness model.

Therefore the aim of this article is to provide a general methodology of statistical fracture toughness models based on functional Weibull forms, feed by heterogeneous databases, that:

- a) encompasses the MC methods using richer statistical models;
- b) solves the coherency problem raised by thickness correction when using such models;
- c) allow to incorporate the majority of experimental data and;
- d) provide adapted tools to model selection previous to the computation of functions of interest, as a brittle rupture reference temperature.

More precisely, the article is written as follows. Section 2 is dedicated to a brief presentation of the experimental context, a short reminder of the MC methodology and the proposed statistical methodology itself. It includes a data modelling step and the choice of appropriate functional forms $\{\alpha(T), K_{\min}(T), K_0(T)\}$ generalizing (1). The appropriate prior selection and statistical assessment of a class of toughness models, through the development of a specific genetic algorithm, is considered in Section 3. Section 4 describes the most adapted statistical methods for comparing the assessed models. The methodology is then applied to simulated and observed datasets, by means of the WOLF3 software [31]. Finally, main results, remaining issues and future research avenues are summarized and discussed in a dedicated section.

2. STATISTICAL MODELLING OF FRACTURE TOUGHNESS DATA

The realization of a fracture toughness random variable $K_{IC} = K_{i,T}$ at a given temperature T can be produced by destructive experiments based on a mechanical stress imposed on a pre-cracked specimen [47, 46]. The major feature of a specimen i is its thickness $B_{i,T}$, which typically evolves between 25 mm and 100 mm. Toughness is determined for a reference thickness B_0 (25 mm according to the ASTM norm [5]) and is assumed to follow, according to

the WL theory, the three-parameter Weibull distribution (1). The heterogeneity of specimen thicknesses can be discarded using the scale invariance property of the (reduced) two-parameter Weibull distribution, by the following transformation of the original samples:

$$K'_{i,T} = K_{\min} + (K_{i,T} - K_{\min}) \times \left(\frac{B_{i,T}}{B_0} \right)^{\frac{1}{\alpha}}, \quad (3)$$

provided (α, K_{\min}) are known. The first step of the MC methodology [35], assuming $\alpha = 4$ and $K_{\min} = 20 \text{ MPa}\cdot\text{m}^{1/2}$ is to produce this transformed sample. The estimation of $\{b_1, b_2, b_3\}$ follows. However, assuming an encompassing statistical framework for the MC model requires that $\{\alpha, K_{\min}\}$ should be estimated in parallel to $\{b_1, b_2, b_3\}$. While several authors (as [22]) prefer to make this correction before estimation, a more appropriate and fair estimation of $\theta = \{\alpha, K_{\min}, b_1, b_2, b_3\}$ should be based on maximizing the statistical likelihood defined, for one original data $k_{i,T}$, by

$$f_{K_{IC}}(k_{i,T}) = \left(\frac{\alpha}{(K_0 - K_{\min})(T)} \right) \times \left(\frac{k_{i,T} - K_{\min}(T)}{(K_0 - K_{\min})(T)} \times \left(\frac{B_{i,T}}{B_0} \right)^{\frac{1}{\alpha}} \right)^{(\alpha - 1)} \times \exp \left(- \left[\frac{k_{i,T} - K_{\min}(T)}{(K_0 - K_{\min})(T)} \times \left(\frac{B_{i,T}}{B_0} \right)^{\frac{1}{\alpha}} \right]^{\alpha} \right). \quad (4)$$

83 The measurements generally considered as correct [20] are those referred to as K_{IC} ,
 84 obtained by the procedure specified in ASTM E399-90, and the indirect K_{JC} elasto-plastic
 85 energy measurements which attempt to mitigate non-compliance with the linear constraints
 86 required by the mechanical theory (applied for obtaining K_{IC} to be valid).

87

88 In addition, empirical data can be obtained for different sample sizes and test temperatures
 89 which correspond to limit values (upper or lower bounds) for a *missing* toughness observation
 90 according to the classification by [20]. Such data can typically correspond to experiments
 91 conducted in the ductile range, without complete cracking, or, alternatively, by experiments
 92 “leading to large-scale yielding, exceeding the specimen’s measuring capacity limit” [46].
 93 Such data yield *censoring* information that is statistically relevant [3]. Most data referred to
 94 as K_{CM} , K_{CPM} and K_{MAX} in international nomenclatures [46, 51, 33] originate from quasi-
 95 valid experiments and may be considered as minimum limits (*right-censored*) for a missing
 96 toughness value. The likelihood contribution of a $k_{cm,i,T}$ (or $k_{jc-lim,i,T}$, etc.) value is then

$$P(K_{IC} > k_{cm,i,T}) = \exp \left(- \left[\frac{k_{cm,i,T} - K_{\min}(T)}{(K_0 - K_{\min})(T)} \times \left(\frac{B_{i,T}}{B_0} \right)^{\frac{1}{\alpha}} \right]^{\alpha} \right). \quad (5)$$

97 Conversely, other data referred as K_{JC-lim} correspond to going beyond the range of relevance

98 of toughness measurements and constitute upper limits (*left-censored*) for the expected
99 toughness value. The statistical likelihood term of such a value obtained with a test specimen
100 of thickness $B_{i,T}$ at a test temperature of T is then

$$P(K_{IC} < k_{jc-lim,i,T}) = 1 - \exp \left(- \left[\frac{k_{jc-lim,i,T} - K_{min}(T)}{(K_0 - K_{min})(T)} \times \left(\frac{B_{i,T}}{B_0} \right)^{\frac{1}{\alpha}} \right]^{\alpha} \right). \quad (6)$$

101 Incorporating both the thickness correction and the addition of censored values in the
102 toughness statistical assessment is, by itself, an innovation in the field of fracture mechanics.
103 Furthermore, more versatility can be given to the statistical model by considering several
104 possible functional forms for the unknown parameter vector θ in function of T : apart from
105 being constant, each component θ_k can be described as an increasing function of T (respecting
106 the typical banana shape of toughness distribution, as in Figure 1). With $(a_k, b_k, c_k) \in \mathbb{R}_*^+$,
107 the selected functions are:

- 108 1. linear: $\theta_k = a_k + b_k \times T$;
- 109 2. quadratic: $\theta_k = a_k + b_k T + c_k T^2$;
- 110 3. exponential: $\theta_k = a_k \exp(b_k T)$;
- 111 4. shifted exponential: $\theta_k = a_k + b_k \times \exp(c_k T)$.

112 Next section is dedicated to the prior selection of these functional models, for each dimension
113 θ_k , then the overall fitting of the prior selected models using the likelihood maximum
114 principle. Once the estimations conducted, a phase of posterior model selection is required
115 to select the best candidate. This will be considered in Section 4.

3. PRIOR MODELS CLASS SELECTION AND STATISTICAL ASSESSMENT

116 The functional forms described above generate a wide range of possible encompassing
117 statistical models that should be restrained before conducting parallel assessments. Only the
118 most appropriate forms a priori must compete to explain the observations then be selected
119 by statistical methods. Therefore a first step of the methodology, fully implemented within
120 the WOLF3 software [31, 30], is to select these appropriate forms, using local estimation
121 principles. Then an overall fitting is conducted. It should be noticed that, while the censored
122 observations carry information to this second task, they are not used for the first one, since
123 they cannot help to discriminate between forms unlike toughness data considered as correct.

3.1. Selection of appropriate functional models by local estimation

124 When toughness values are highly dispersed in relation to temperature, Weibull parameters
125 must be estimated over a reduced temperature range and estimation must be conducted in
126 relation to the reference temperature for this range. This reference temperature is either the
127 mean temperature or the median temperature. In order to process the entire temperature
128

129 range of the database, two types of toughness data sub-sampling are carried out, based
 130 on a subdivision of the temperature range such that each sub-sample of data corresponds
 131 to the associated data in a sub-range of temperature: sequential sub-sampling and sliding
 132 sub-sampling. Weibull parameters are then estimated for each sub-sample. With the local
 133 estimates obtained, a functional temperature model can then be selected for each component
 134 of θ .

135
 136 *Sequential sup-sampling* involves subdividing the temperature range I_T of the database
 137 into N separate consecutive sub-ranges $(I_i)_{i=1,\dots,n}$ with the same thermal amplitude ΔT .
 138 Alternatively, *sliding sub-sampling* involves subdividing the temperature range I_T of the
 139 database into N consecutive sub-ranges ΔT . We then have to build an initial temperature
 140 range I_1 starting with the lowest temperature T_1 of the temperature range up to temperature
 141 $T_1 + \Delta T$ and the next sub-range I_2 is obtained by sliding the sub-range I_1 by a shift of dT .
 142 Accordingly, $I_2 = [T_1 + dT, T_1 + dT + \Delta T]$. This operation is repeated until the sub-range
 143 I_n reaches the maximum temperature of I_T .

144
 145 *Local estimations* follow. For a fixed T , Weibull parameters α, K_{\min} and $K_0 - K_{\min}$ are
 146 estimated for each of the N_D sub-ranges obtained by sequential or sliding sub-sampling. The
 147 following methods are considered, that take into account the thickness for each toughness
 148 value.

- 149 1. *The moment method*: for all α (shape parameter) varying in the interval $[a; b]$ with a
 150 step h , the estimation of $K_0 - K_{\min}$ and K_{\min} is conducted by the method of moments
 151 [12]. Only the triplets $(\alpha, (K_0 - K_{\min})^*, K_{\min}^*)$ having a physical sense are retained;
- 152 2. *The maximum likelihood method* consists in searching the values of the parameters
 153 that maximize the likelihood function, for the three-parameter Weibull distribution:
 154 following Smith and Lawless' advice [39, 24] for all K_{\min} (position parameter) varying
 155 in the interval $[a; b]$ with a step h , the estimation of the parameters α and $K_0 - K_{\min}$
 156 is conducted by the maximum likelihood method. The triplet $(\tilde{\alpha}, (K_0 - K_{\min})^*, K_{\min}^*)$
 157 which maximizes the complete likelihood is selected;
- 158 3. *A hybrid method* for the Weibull distribution which combines the previous ones: the
 159 K_{\min} parameter is estimated by the moment method and then others are estimated by
 160 the maximum likelihood method.

161 The moment and maximum likelihood methods produce several triplet solutions which are
 162 hierarchized using Cramer-Von Mises, Kolmogorov-Smirnov and Anderson-Darling criteria
 163 [40]. In each test, the triplet minimizing the associated statistical value is selected. Finally,
 164 N_D local estimates $(\alpha^*, (K_0 - K_{\min})^*, K_{\min}^*)_{i=1,\dots,N_D}$ are obtained, where N_D is the number
 165 of sub-samples. These samples allows for a graphical evaluation of the relevance of functional
 166 forms described in previous section, as well as fitting using usual least-square techniques.

167 3.2. Maximum likelihood overall estimation

168 This second step consists in calculating the best functional estimates $(\alpha^*(T), (K_0 -$
 169 $K_{min})^*(T), K_{min}^*(T))$ by maximizing the overall likelihood defined as

$$\begin{aligned} \mathcal{L}_{K_{min}, \alpha, (K_0 - K_{min})}(\mathbf{k}) &= \mathcal{L}_1(K_{min}, \alpha, (K_0 - K_{min}))(\mathbf{k}_{1C}) \\ &\quad \times \mathcal{L}_2(K_{min}, \alpha, (K_0 - K_{min}))(\mathbf{k}_r) \\ &\quad \times \mathcal{L}_3(K_{min}, \alpha, (K_0 - K_{min}))(\mathbf{k}_l), \end{aligned}$$

170 where $\mathbf{k} = \{\mathbf{k}_{1C}, \mathbf{k}_r, \mathbf{k}_l\}$ denotes all data produced by experiments, \mathbf{k}_{1C} being the regular
 171 toughness data while \mathbf{k}_r (*resp.* \mathbf{k}_l) are the right-censored (*resp.* left-censored) observations.
 172 Assuming the independence of measurements, the corresponding likelihoods \mathcal{L}_1 , \mathcal{L}_2 and
 173 \mathcal{L}_3 are products of terms described in Section 2. Replacing α , $(K_0 - K_{min})$ and K_{min} in
 174 $\mathcal{L}_{K_{min}, \alpha, (K_0 - K_{min})}(\mathbf{k})$ by functionals $\alpha(T)$, $(K_0 - K_{min})(T)$ and $K_{min}(T)$ parametrized by
 175 $(a_i, b_j, c_l)_{i \in I, j \in J, l \in L}$, the optimisation problem becomes to estimate

$$\begin{aligned} (a_i, b_j, c_l)_{i,j,l}^* &= \arg \max \log \mathcal{L}_{K_{min}(T), \alpha(T), (K_0 - K_{min})(T)}(\mathbf{k}) & (7) \\ &\text{under the constraints} \\ \alpha(T) &> 2 \quad \forall T, \\ (K_0 - K_{min})(T) &> 0 \quad \forall T, \\ 0 < K_{min}(T) &< \min_{(i,T) \in \mathbf{k}_{1C}} k_{(i,T)}. \end{aligned}$$

176 Genetic algorithms [28] are general-purpose search algorithm based upon the principles
 177 of evolution in nature (permanent adaptation). They can be applied to a wide variety of
 178 optimisation problems [16] and appeared of good relevance to solve (7). For nonregular
 179 models, compact sets for the variation ranges of coefficients to be estimated usually appear
 180 necessary to obtain non-degenerate and consistent MLE [39], in addition of other constraints
 181 (for instance, the true value of α should be upper than 2 when considering a nonfunctional
 182 three-parameter Weibull distribution [50]). More generally, it is a prerequisite for starting
 183 genetic algorithms. In the WOLF3 software, such ranges can be directly informed by the
 184 user or provided by a bootstrap algorithm, described hereafter. In numerical experiments
 185 these ranges were found to contain the true value for each coefficient, but obviously this
 186 cannot be guaranteed in all situations.

189 Non-parametric bootstrap calibration of variation ranges.

- 190 1. Sample with replacement N_{Boot} datasets $\{d_1, \dots, d_{N_{Boot}}\}$, each of size
- 191 N , amongst the N (uncensored) original toughness observations;
- 192 2. For replicate d_i , produce $k_i < N$ local estimations of $\{\alpha, K_{min}, K_0 -$
- 193 $K_{min}\}$ and fit the parametric model chosen for each parameter;
- 194 3. Estimate empirically the quartiles $\{q_{k,1}, q_{k,2}, q_{k,3}\}$ from the N_{Boot} -sized
- 195 sample of estimates for each coefficient θ_k ;

4. Calibrate the range for θ_k as

$$[q_{k,2} - 3 \cdot (q_{k,3} - q_{k,1}) \quad q_{k,2} + 3 \cdot (q_{k,3} - q_{k,1})].$$

196 The genetic algorithm proposed in this article is based on the definition of a population
197 of N_p individuals. Each individual represents a point in the space of states which means a
198 candidate solution. It is characterized by a set of genes (the values of the variables to be
199 estimated) and a fitness function (the value of the criterion to be optimized). The algorithm
200 then generates populations at each iteration, on which selection and mutation processes are
201 applied, the purpose of which is to ensure that the space of states is efficiently explored.
202 The evolution of all individuals over several generations leads to the optimum states for the
203 relevant optimisation problem.

204
205 The entire process is carried out for a constant population size and each iteration is referred
206 to as a generation by analogy with genetics. A population initially built by random sampling
207 evolves from a k generation to a $k + 1$ generation by applying the following operations to
208 the individuals:

- 209 • **Evaluation:** in calculating the fitness of the individuals to the problem solution,
210 $\mathcal{L}(K_{min}, \alpha, (K_0 - K_{min}))(\mathbf{k})$ is calculated for genes corresponding to the coefficient
211 values of functional $\alpha(T)$, $(K_0 - K_{min})(T)$ and $K_{min}(T)$. However, if the constraints
212 of Problem (7) cannot be satisfied due to the genes of an individual, its fitness is fixed
213 at $-\infty$.
- 214 • **Selection:** designates the individuals best adapted to survive and transmit their genes
215 in relation to their fitness.
- 216 • **Crossing:** allows genes from two individuals to be mixed to give two offspring
217 individuals intended to replace them.
- 218 • **Mutation:** modifies a gene for certain randomly sampled individuals.

219 The algorithm can be stopped when the population ceases to evolve or for a fixed number
220 of generations. The individual showing the greatest fitness in the final population then
221 corresponds to a solution to the problem.

4. FINAL MODEL SELECTION

222 It must be noticed that the class of models defined in Section 2 encompasses the MC
223 model and other nested models, which implies that statistical testing between assessed
224 models can be conducted using powerful tools as likelihood ratio tests [17]. See Appendix
225 B for an example considering several relaxations of the MC model. Structural differences
226 between linear and exponential functions require that other tools of model selection be
227 used, as Aikake (AIC) and Bayesian (BIC) Information Criteria [1, 36] adapted to censored
228 situations [41, 26?]. In practice, AIC should be preferred since it was conceived to be
229 efficient in a finite list of approximate models, optimizing the trade-off between bias and

230 variance [8], while BIC (known to select models with smaller dimension than AIC, possibly
 231 underfitted) is consistent in the sense it selects (asymptotically) the true model in a class
 232 if it is assumed to be unique and belong to this class [9]. In addition, a conditional χ^2 test
 233 was specifically developed to help selecting the most relevant model among all tested ones,
 234 from the uncensored observations. A summary of this procedure is presented below, while
 235 the details can be found in [30].

236
 237 Considers a set $\{K_{IC}^{(q)}, T^{(q)}\}_{q=1, \dots, n}$ of toughness measures and indexation temperatures
 238 and assume that all data pairs are mutually independent. The fitness of a traditional χ^2
 239 test [48] to this set of pair of variables requires a subdivision of the space of the variable
 240 $K_{IC}|T = x$ into L classes S_l (*cf.* Figures 2 and 3). Then the L -sized observation vector
 241 N_{obs} is compared to the L -sized theoretical vector N_{exp} , both defined as:

$$N_{obs} = \begin{pmatrix} \sum_{q=1}^n \mathbb{1}_{K_{IC}^{(q)} \in S_1} \\ \vdots \\ \sum_{q=1}^n \mathbb{1}_{K_{IC}^{(q)} \in S_L} \end{pmatrix} \quad \text{and} \quad N_{exp} = \begin{pmatrix} \sum_{k=1}^K n_k q_{1,k} \\ \vdots \\ \sum_{k=1}^K n_k q_{L,k} \end{pmatrix}$$

243 where, $\forall l \in \{1, \dots, L\}$ and $\forall k \in \{1, \dots, K\}$,

$$q_{l,k} = \mathbb{P}(K_{IC} \in S_l | T = x_k),$$

244 and n_k is the number of times when $T = x_k$.

245 [Figure 2 about here.]

246 [Figure 3 about here.]

247 Finally,

$$Z = N_{obs} - N_{exp} \sim \mathcal{N}_L(0, \Gamma)$$

with

$$\Gamma = n \begin{pmatrix} \sum_{k=1}^K n_k q_{1,k} [1 - q_{1,k}] & - \sum_{k=1}^K n_k q_{1,k} q_{2,k} & \cdots & - \sum_{k=1}^K n_k q_{1,k} q_{L,k} \\ - \sum_{k=1}^K n_k q_{2,k} q_{1,k} & \sum_{k=1}^K n_k q_{2,k} [1 - q_{2,k}] & \cdots & - \sum_{k=1}^K n_k q_{2,k} q_{L,k} \\ \vdots & \vdots & \ddots & \vdots \\ - \sum_{k=1}^K n_k q_{L,k} q_{1,k} & - \sum_{k=1}^K n_k q_{L,k} q_{2,k} & \cdots & \sum_{k=1}^K n_k q_{L,k} [1 - q_{L,k}] \end{pmatrix}$$

248 where K is the number of distinct values of T .

$$U \Sigma^{-1} U' \sim \chi_Q^2$$

249 Noting Z^* the vector containing only the first $L - 1$ components of Z and Γ^* its covariance
250 matrix (i.e. the matrix Γ without the last column and the last line), it comes, under the null
251 hypothesis H_0 that the tested model is true:

$$Z^* (\Gamma^*)^{-1} Z^{*'} \sim \chi_{L-1}^2$$

252 and H_0 will be rejected at threshold ϵ if the test statistic $Z^* (\Gamma^*)^{-1} Z^{*'}$ exceeds the percentile
253 $\chi_{L-1}^2(1 - \epsilon)$.

5. NUMERICAL EXPERIMENTS

254 The following numerical experiments are conducted from a so-called EURO database of 849
255 real steel (16 MDN5) toughness measurements (Figure 1), aggregating data from different
256 European manufacturers or exploiters (SIEMENS, EDF, CEA, FRAMATOME, AEA).
257 Various versions of this database, according to whether or not it includes toughness data
258 considered as quasi-valid, non-valid but informative or poorly informative, were used in [20]
259 and [22].

260
261 Sequential sub-sampling based on a $20^\circ C$ width, involving a minimum of 20 data per
262 sample, was conducted on the regular data (Figure 4). By local estimation using the method
263 of moments on each sub-sample, $N = 7$ triplets $(K_{min}^{(i)}, \alpha^{(i)}, K_0^{(i)} - K_{min}^{(i)})_{i=1, \dots, N}$ are assessed.
264 In Figure 4, the local estimates are fitted by a linear function for $K_{min}(T)$, a constant value
265 for $\alpha(T)$ and a shifted exponential function for $(K_0 - K_{min})(T)$.

266

[Figure 4 about here.]

267

268 An overall ML estimation was conducted, gradually increasing the data size. The results
269 are set out in Table 1. Divergences standardised between empirical and theoretical quantiles
270 are also traced (QQ-plots, cf. Figures 7 and 8) and summarised in the same table, focusing
271 separately on the high and low sections of the transition curve. Taking into account
272 censoring information, the estimated model provides mean deviation between empirical
273 and theoretical quantiles which is almost 6% better for all quantiles together, almost 9%
274 better for high quantiles (75%-99%) and almost 2% better for low quantiles (0.1%-25%) in
275 relation to the dispersion found when censoring is not taken into account. Hence, including
276 the censoring information increases the information on the toughness model parameters
277 coherently with the structure of the model. The relevance of the estimations summarized in
278 Table 1 is verified by performing simulated tests in next two subsections.

280 [Table 1 about here.]

281 [Figure 5 about here.]

282 5.1. Initial experiments

283 30 sets of 849 values each were simulated from the following estimates, which are very
284 similar to those obtained from the EURO database: $K_{\min} = 20$, $\alpha = 3$ and $K_0(T) - K_{\min} =$
285 $0.004 + 424 \cdot \exp(0.01472 \cdot T)$. The test temperatures are the same as those in the original
286 dataset and every dataset complies with the proportion of censored data in the latter (4.4%
287 right-censored, 59% left-censored). Additional details about the features of the simulation
288 process are given in Appendix A.

289 Table 2 summarizes the estimation results. All simulated values of the parameters
290 are located within the standard confidence ranges built from the estimators. Note in
291 particular that the standard deviation of the estimator on the ordinate at the origin of
292 $K_0(T) - K_{\min}(T)$ puts into perspective the difference observed between the simulated value
293 and the average estimate obtained from the 30 samples. The estimation procedure presented
294 in this article and implemented in the WOLF3 software [31, 30] thus provides relevant results
295 and, in particular, gives a good estimate of the brittle phase (the ordinate at the origin of
296 $K_{\min}(T)$).

297 [Table 2 about here.]

298 5.2. Subsequent experiments

299 Secondly, testing is required to establish whether a more complex model encompassing the
300 traditional MC is accurately estimated if the simulated data actually come from a MC: the
301 additional parameters must be estimated at 0 or near to 0 and the more flexible models must
302 adopt a similar behavior. Accordingly, by Ockham's rule of least complexity and on the basis
303 of statistics from traditional testing procedures (e.g., AIC), the simplest model most used in
304 practice should be selected.

305 The simulation parameters are therefore chosen as follows: $K_{\min} = 20$, $\alpha = 4$ and $K_0(T) -$
 306 $K_{\min} = 50 + 200 \cdot \exp(0.002 \cdot T)$, and the test temperatures and censoring values are selected
 307 as previously. Again, 30 independent datasets are simulated, of which an example is shown
 308 in Figure 10 (in Appendix). The estimation results are shown in Table 3. The assumption
 309 $\alpha = 4$, essentially characteristic of the Master Curve, is applied by these models. The low
 310 level of linearity noted for K_{\min} has little effect on the shape of the curve and, for its part, the
 311 parameter that determines the exponential shape is well-estimated. Additional complexity
 312 (passing from a linear model to a shifted exponential model for K_{\min} is logically manifested
 313 in increased estimated standard deviation values. However, through limited development,
 314 the low value of the exponential coefficient of K_{\min} allows an equivalent linear model to be
 315 obtained and the brittle phase to be quantified between 20 and 25 $MPa \cdot \sqrt{m}$. As expected,
 316 this brings us back to the main features of the Master Curve.

317 [Table 3 about here.]

318 5.3. Testing the Master Curve in the EURO database

319 Finally, the statistical relevance of the classic MC model over the motivating EURO dataset
 320 is compared to the other possible models defined by the encompassing framework. Results
 321 of fitting are summarized on Tables 4 (including the MC model) and 5. The AIC criterion
 322 is defined classically [1] as the penalization of twice the maximized negative loglikelihood:

$$\text{AIC} = -2 \log \mathcal{L}_{\hat{\theta}}(\mathbf{k} + 2d)$$

323 in the uncensored case, with d the dimension of the model, \mathcal{L} its likelihood and $\hat{\theta}$ the MLE
 324 of the unknown parameter vector θ , and

$$\text{AIC} = -2 \log \mathcal{L}_{\hat{\theta}}(\mathbf{k} + d + \text{tr} \left(I_{\text{all}, \hat{\theta}} I_{\text{incomp}, \hat{\theta}}^{-1} \right)) \quad (8)$$

325 in the censored case, following [?], where $(I_{\text{all}, \theta}, I_{\text{incomp}, \theta})$ are the Fisher information matrices
 326 for the complete data and incomplete data, respectively defined by (for a single observation
 327 k)

$$I_{x, \theta} = - \int \mathcal{L}_{\theta}^x(k) \frac{\partial^2 \log \mathcal{L}_{\theta}^x(k)}{\partial \theta \partial \theta^T} dk,$$

328 where $x \in \{\text{incomp}, \text{all}\}$ and where $\mathcal{L}_{\theta}^{\text{incomp}}$ is either the density, the survival of the cumulative
 329 distribution function in k , while $\mathcal{L}_{\theta}^{\text{all}}$ is only the density of k . For these functional models
 330 these information quantities can be empirically computed from the observations. It was
 331 most often observed that, for the considered dataset, the extreme-right penalty in (8) was
 332 very close to d . This formulation means that a model with a low AIC value is considered to
 333 explain better the observations than a model with a high AIC value.

334
 335 The results first confirm the necessity of relaxing the rigidity of the MC model, by
 336 considering more parameters are unknown a priori and conducting statistical estimation.

337 A negligible p -value of the χ^2 test (namely, a negligible probability of observing the test
338 statistic under the assumption of the model in consideration), associated to a high AIC value,
339 highlight that the MC model is comparable, in terms of explicative power, to basic models
340 based on linear functionals only. The sensible gap in terms of AIC due to the insertion of
341 a shifted exponential model with unknown parameters, for K_{\min} or $K_0 - K_{\min}$ (provided
342 other parameters are unknown too), indicates that a good strategy for selecting a relevant
343 model should at least take account of this criterion. Using a LRT test described in appendix
344 B, it is possible to refine the diagnostic about the MC model: considering the relaxed MC
345 model with unknown (but constant) K_{\min} and α (with operational constraints $K_{\min} \geq 10$
346 and $\alpha > 2$), the observed statistic is $R_{4,1} \simeq 0.04923$ which is of the same order than the
347 5%-order percentile of the mixture of Dirac and χ^2 distributions ($\simeq 0.05375$).

348 If the quadratic evolution of $K_0 - K_{\min}$ seems to be the most relevant from the AIC
349 viewpoint at the light of the results provided on both tables, a quick look on the
350 corresponding figures (Figures S-15 and S-21 in Supplementary Online Material (SOM)) is
351 enough to discard such a model from a physical point of view (no observation is plausible at
352 low temperature close to $100 \text{ MPa} \cdot \sqrt{m}$). Rather, a good trade-off between statistical fitting
353 and physical plausibility is provided by Models (14) and (17). The estimation of parameters
354 (see Figures S-27, S-28 and S-33 in SOM) shows that the quadratic and exponential
355 coefficients of K_{\min} take most often very small values, and that these models can be easily
356 derived (by Taylor expansion around 0) in the simpler form of Model (12), which is our
357 final choice for this dataset. Note that the standard MC model and Model (12) strongly
358 differ by their derived value of the reference temperature (gap $\sim 10^\circ\text{C}$). Another important
359 consequence is that the brittle stage K_{\min} is increasing with the temperature. Such a result
360 appears to be useful for risk engineers who would be able to define sensitivity analyses and
361 margin assessments with respect to the conservative MC model.

362
363 Finally, it must be noticed that accounting for censored values can have a more sensible
364 effect on the estimation of unknown parameters and (as expected) on the reference
365 temperature, traduced by a possible difference of several degrees, than on the model selection
366 itself.

367 [Table 4 about here.]

368 [Table 5 about here.]

6. DISCUSSION

369 This article presents a statistical methodology of estimation and selection of a class of steel
370 fracture toughness models encompassing the celebrated Master Curve. Its implementation
371 within a dedicated software was thought to simplify its use by reliability engineers. The
372 common practice of this engineering field, as crude homogenization of experimental data
373 and putting aside nonregular observations, as well as the practical necessity of using more
374 flexible models than the Master Curve, motivated this work. An immediate benefit of

375 improving the statistical modelling of steel fracture toughness is improving the knowledge of
376 the brittle stage and the brittle-ductile transition temperature range. While the brittle stage
377 appears as a penalizing factor in structural reliability studies, the reference temperature
378 can be used to hierarchize steels and compare steel structures.

379
380 Another interest of this refined modelling is guiding the design of new destructive
381 experiments (while the use of censored observations yields supplementary information that,
382 conversely, should diminish the necessity of such experiments). Indeed, designing these
383 experiments is realizing a trade-off between costs and statistical information gain, through
384 the use of cost functions and information measures integrated over the expected distribution
385 of toughness [15]. In a Bayesian perspective, a prior model recognized as “the best on
386 the market” can be used to derive accurate distributions for the coefficients and delimit
387 the most informative ranges of temperature to explore, under fixed budget, to improve
388 significantly the robustness of the statistical modelling [10]. This will be the subject of a
389 future work.

390
391 This methodology remains clearly opened to improvements. First, the selection of
392 functionals based on local estimations may suffer from a lack of estimated parameter values
393 if the temperature ranges are chosen too wide. Using nonregular ranges to gain estimations
394 may distort the estimated shapes and bias the selection of these functionals. Nonparametric
395 tests could besides be adapted to provide objective help to this selection. Second, the overall
396 optimisation task could probably be improved by taking account of the missing data structure
397 due to the presence of censoring, using multiple imputation methods or data augmentation
398 methods. Finally, the use of sensitivity analysis techniques [21] could be helpful for comparing
399 the robustness of several assessed models, in complement to classic criteria, and improving
400 the confidence that may be placed in the modelling of this very influential input of structural
401 reliability studies.

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APPENDIX

A. SIMULATION OF EXPERIMENTAL DATASETS

511 A particular attention was paid to check that each of the 30 sets simulated in § 5.1 reproduce
512 accurately the main features of the real EURO database. These data were simulated in
513 compliance with a criterion of observed “distance” between regular and censored data in the
514 original dataset. Let us consider a censored value $k_1(T_1)$ in the original dataset. For a small
515 relative difference $\Delta_{T_2} = T_2/T_1 - 1$ between test temperatures, a small relative difference in
516 the toughness value $\Delta_{K(T)} = K(T)/k_1(T_1) - 1$ and the small relative difference in the size of
517 the test piece $\Delta_{B_T} = B(T)/b_1(T_1) - 1$, we define as a valid data the nearest value $k_2(T_2)$ to
518 the direction of the experimental conditions by means of the following least weighted squares
519 criterion:

$$k_2(T_2) = \arg \min_{k(T)} \{ \omega_1 \Delta_T^2 + \omega_2 \Delta_{k(T)}^2 + \omega_3 \Delta_{B_T}^2 \} \quad (9)$$

520 where $\{\omega_1, \omega_2, \omega_3\}$ are positive weights summing to 1. A Wilcoxon homogeneity statistical
521 test [49] based on the closeness of the samples simulated in this way and the original sample
522 showed that the first two terms of the above criterion play a major part in selecting a “good”
523 value $k_2(T_2)$. The following choices were applied:

$$\{\omega_1, \omega_2, \omega_3\} = \{0.6, 0.3, 0.1\}.$$

524 The second test, founded on the two first criteria only, specifies a unique solution to the
525 problem (9). The toughness dispersion

$$\Gamma_{k_1(T_1)} = k_1(T_1) - k_2(T_2)$$

526 is used to simulate a censored value $\tilde{k}_2(T_2)$ from a simulated valid value $\tilde{k}_2(T_1)$:

$$\tilde{k}_2(T_2) = \tilde{k}_2(T_1) + \Gamma_{k_1(T_1)}.$$

527 This bootstrapping procedure on the dispersion of toughness values generates datasets that
528 are extremely similar to the original, as shown on Figures 9 and 10. Kolmogorov-Smirnov and
529 Cramer-von Mises tests between truly observed and simulated data were finally conducted
530 conditionally to several temperature values, which did not exhibit surprising behaviors.

531 [Figure 6 about here.]

532 [Figure 7 about here.]

B. TESTING THE RELEVANCE OF THE MASTER CURVE

533 Using the notations defined in (1) and (2), consider the three following toughness models
534 differing by their degree of freedom (θ_i defining the vectors of unknown parameters to

535 estimate) and possible inequality constraints:

$$\begin{aligned}
\text{original Master Curve 1 (MC1):} & \quad \alpha = 4, K_{\min} = 20, \theta_1 = (b_1, b_2, b_3) \in \mathbb{R}_*^+; \\
\text{relaxed MC 2 (MC2):} & \quad \alpha = 4, \theta_2 = (K_{\min}, b_1, b_2, b_3) \in \mathbb{R}_*^+ \text{ and } K_{\min} > 20; \\
\text{relaxed MC 3 (MC3):} & \quad K_{\min} = 20, \theta_3 = (\alpha, b_1, b_2, b_3) \in \mathbb{R}_*^+ \text{ and } \alpha > 2; \\
\text{relaxed MC 4 (MC4):} & \quad \theta_4 = (\alpha, K_{\min}, b_1, b_2, b_3) \in \mathbb{R}_*^+ \text{ and } K_{\min} > 20 \text{ and } \alpha > 2.
\end{aligned}$$

536 Assume to dispose of the various MLE $(\hat{\theta}_i)_{i \in \{1:4\}}$ computed from the same dataset.
537 Likelihood ratio tests (LRT) are one of the most powerful statistical tools [17] for conducting
538 the following tests, that evaluate the statistical relevance of the original Master Curve :

539 **(T1)** H_0 : MC1 versus H_1 : MC2;

540 **(T2)** H_0 : MC1 versus H_1 : MC3;

541 **(T3)** H_0 : MC1 versus H_1 : MC4.

542 Such situations are instances of the general situation when the null hypothesis H_0 is defined
543 by fixing r degrees of freedom of the encompassing model used in the alternative hypothesis
544 (H_1): $r = 1$ in **(T1)** and **(T2)** and $r = 2$ in **(T3)**. Denoting $\mathcal{L}_i(\hat{\theta}_i)$ the likelihood of model
545 MC*i* estimated in its MLE $\hat{\theta}_i$, the asymptotic distribution of the LRT statistic

$$R_{i,j} = 2 \log \frac{\mathcal{L}_i(\hat{\theta}_i)}{\mathcal{L}_j(\hat{\theta}_j)}$$

546 is known under H_0 . This distribution is dependent on r and the number of inequality
547 constraints limiting the domain of definition of the test statistic. Since **(T1)** is equivalent
548 to test if $K_{\min} = 20$ rather than $K_{\min} > 20$, then, assuming the MC hypothesis H_0 is true,
549 the asymptotic distribution of $R_{1,2}$ is a mixture of Dirac δ_0 in 0 and chi-square distribution
550 χ_r^2 with $r = 1$ degree of freedom. More generally, based on Chapter 21 in [17], with n the
551 number of regular observations:

$$\begin{aligned}
R_{1,2}, R_{1,3} & \stackrel{n \rightarrow \infty}{\sim} \frac{1}{2} \delta_0 + \frac{1}{2} \chi_1^2, \\
R_{1,4} & \stackrel{n \rightarrow \infty}{\sim} \frac{\alpha_{14}}{2\pi} \delta_0 + \frac{1}{2} \chi_1^2 + \left(\frac{1}{2} - \frac{\alpha_{14}}{2\pi} \right) \chi_2^2
\end{aligned}$$

552 where $\alpha_{14} = \cos \rho_{14}$ and ρ_{14} is the asymptotic linear correlation coefficient between α and
553 K_{\min} , which can be consistently estimated using the correlation submatrix computed for $\hat{\theta}_4$.
554 Note that an alternative to **(T1)** is simply to test if $K_{\min} = 20$ rather than $K_{\min} > 0$. In
555 such a case, since $\mathcal{L}_2(\hat{\theta}_2)$ remains defined even if $K_{\min} \geq 0$, the Dirac term disappears and
556 an usual χ_1^2 distribution is the asymptotic limit.

557 Additionally, testing H_0 : MC2 versus H_1 : MC4 or testing H_0 : MC3 versus H_1 : MC3 can be
558 similarly conducted, as well as numerous other tests for more complicated functional forms
559 given to α , K_{\min} and $K_0 - K_{\min}$. However, it must be noticed that such tools cannot provide

⁵⁶⁰ a total-ordered testing strategy. Besides, numerous models are not embedded. Consequently,
⁵⁶¹ the LRT-based approach must be completed with other statistical testing procedures.

FIGURES

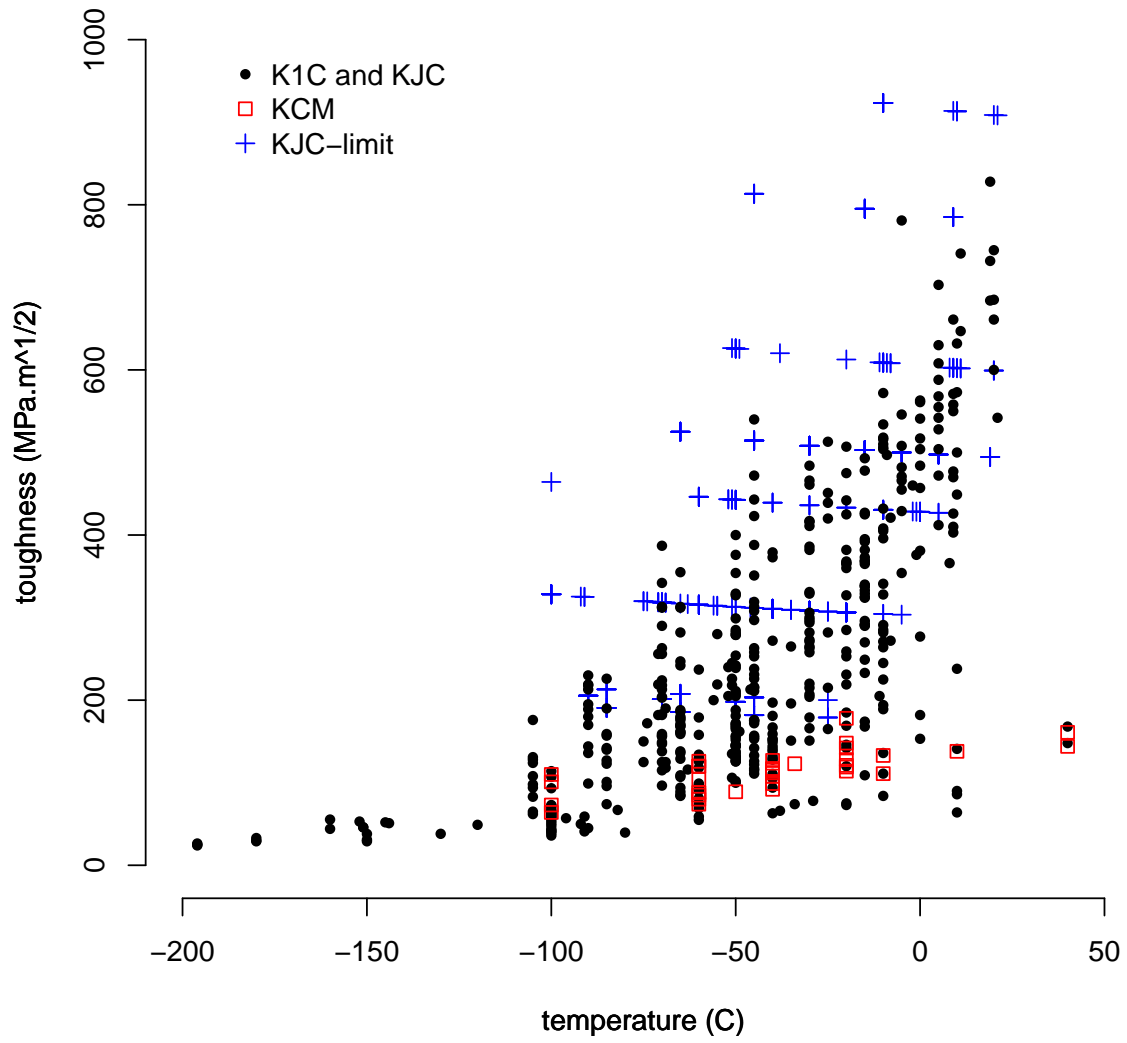


Figure 1. European fracture toughness database.

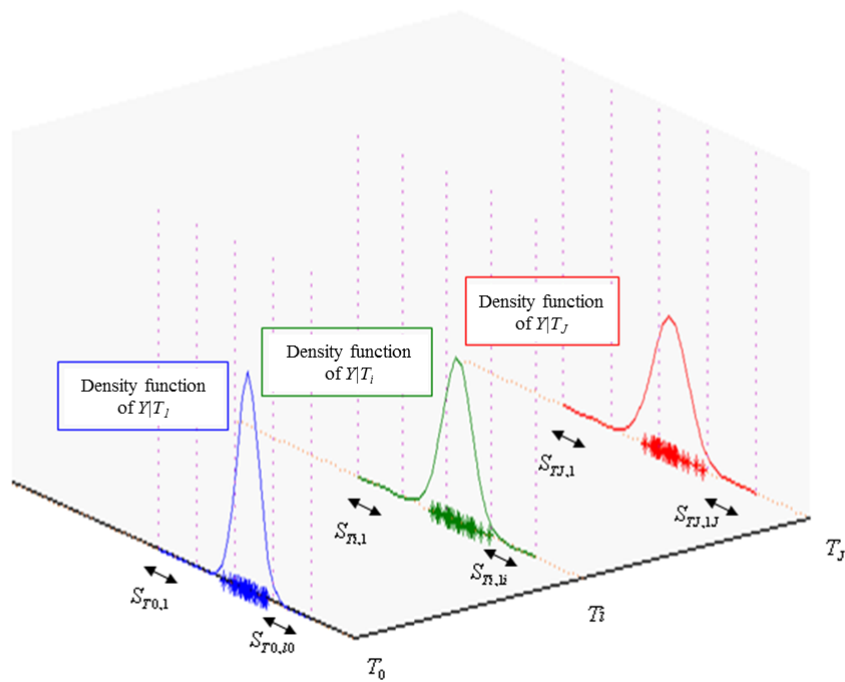


Figure 2. Subdividing the space of the variable $K_{IC}|T$.

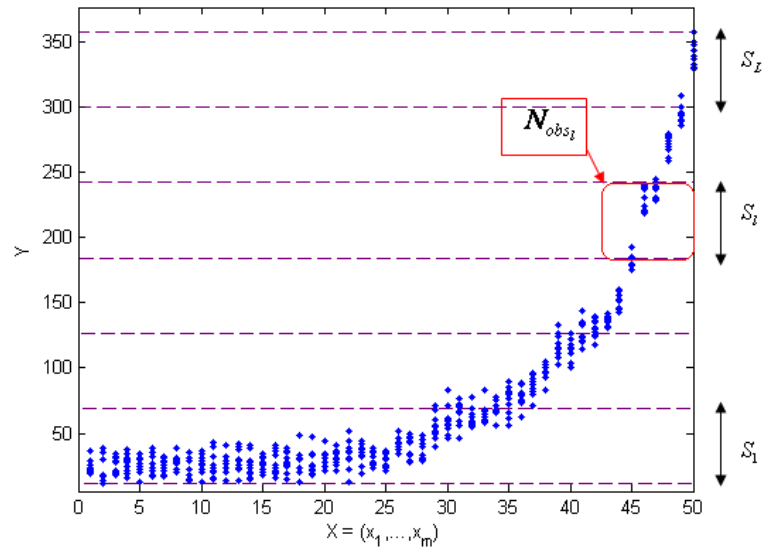


Figure 3. Subdivision of the space of a random variable $Y = K_{IC}$ dependent on a variable $X = T$.

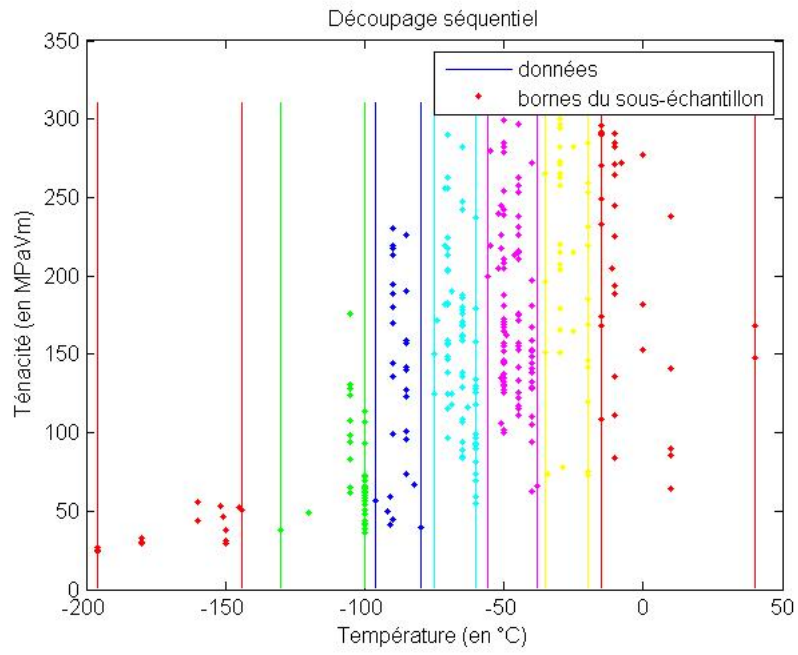


Figure 4. Sequential sub-sampling of the regular data from the EURO database.

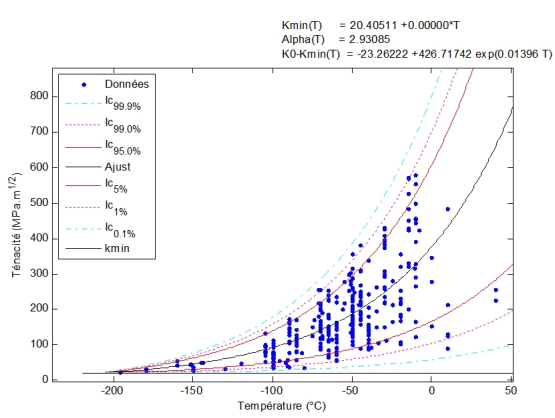


Figure 5. WOLF3 fitting on the European toughness database (valid data only).

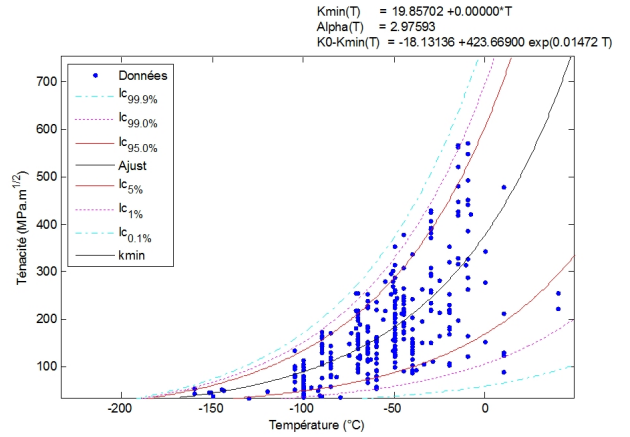


Figure 6. WOLF3 fitting on the European toughness database (all data).

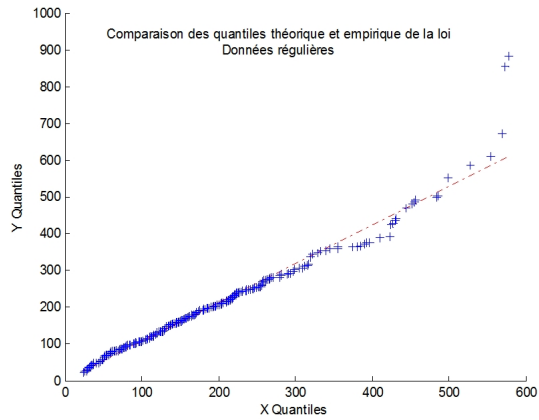


Figure 7. QQ plot of the WOLF3 fitting on the European toughness database (valid data only).

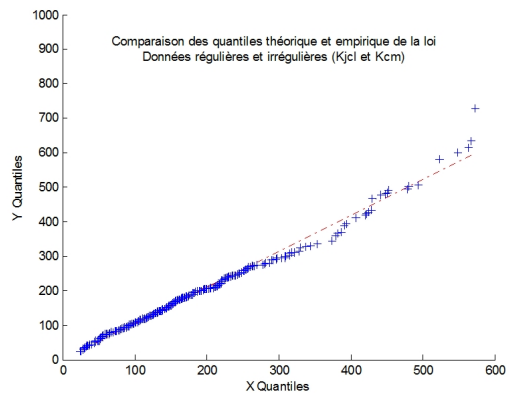


Figure 8. QQ plot of the WOLF3 fitting on the European toughness database (all data).

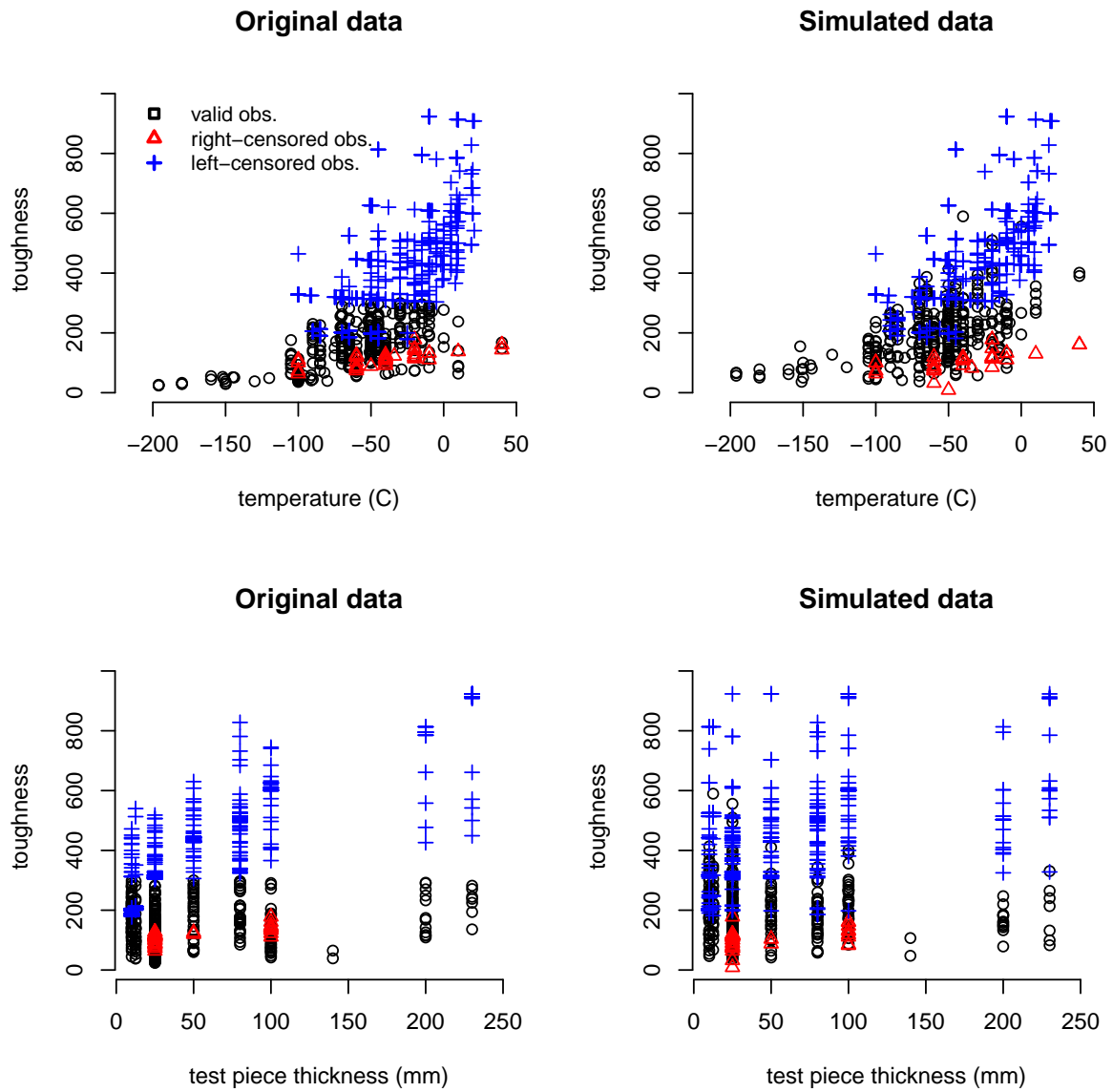


Figure 9. Example of a simulation of a toughness dataset from the EURO database (first experiment).

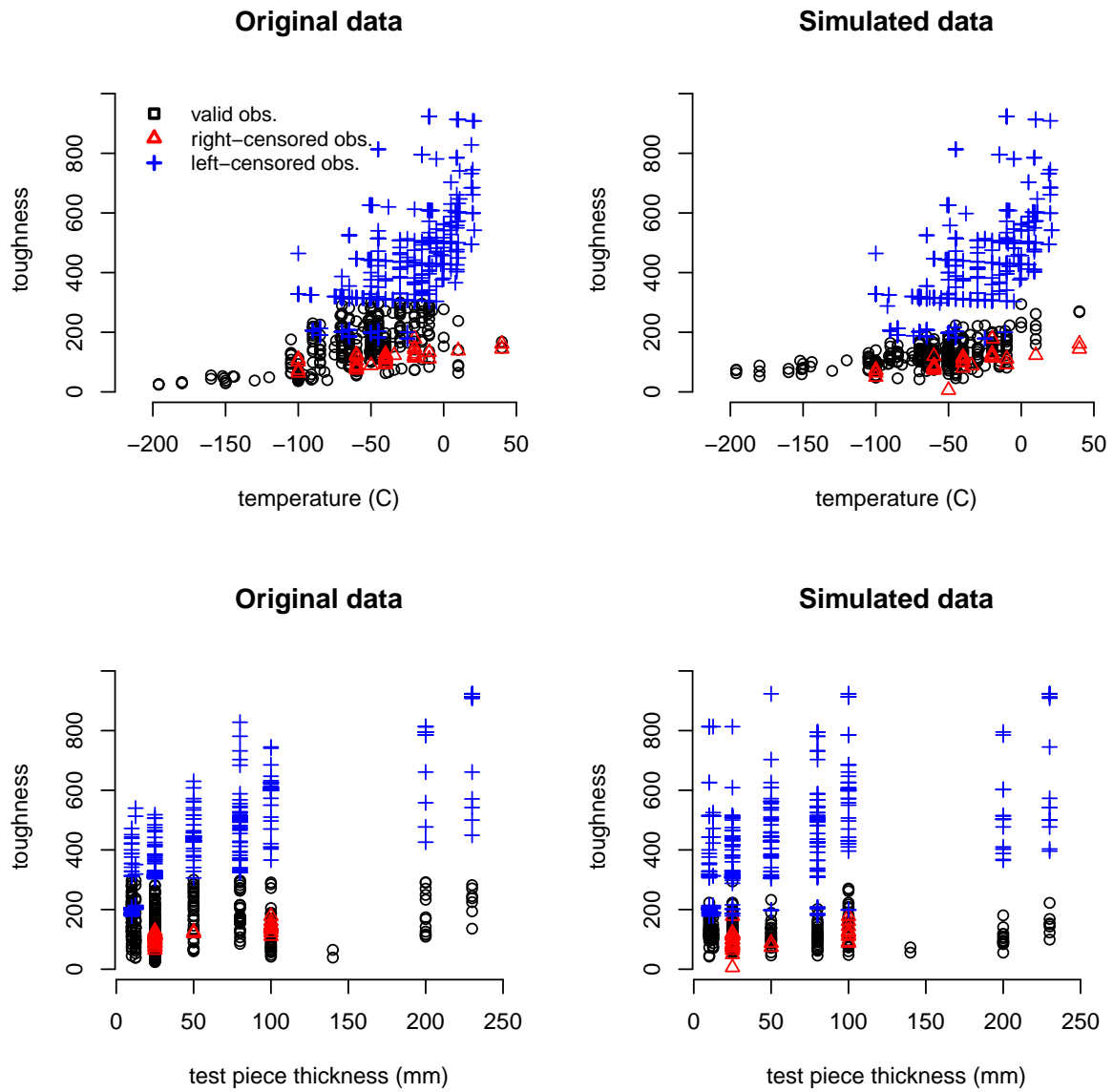


Figure 10. Example of a Master Curve simulation of a toughness dataset from the EURO database (second experiment).

TABLES

	Estimation based on regular data only	Estimation combining all types of data
α	2.78	2.90
$K_{\min}(T)$	$19.78 + 0.013 \cdot T$	$19.85 + 0.048 \cdot T$
$K_0(T) - K_{\min}(T)$	$0.0002 + 484.20 \cdot \exp(0.0186 \cdot T)$	$0.0012 + 463.23 \cdot \exp(0.0175 \cdot T)$
Graphic representation	Fig. 5	Fig. 6
QQ dispersion [0.1% - 99%]	2.30	2.16
QQ dispersion [75% - 99%]	5.81	5.30
QQ dispersion [0.1% - 20%]	2.62	2.57
QQ plot	Fig. 7	Fig. 8

Table 1. Results of estimation by the method of maximum likelihood on the EURO fracture toughness database.

	estimated mean	standard deviation	simulated value
α	3.141	0.12	3
K_{\min} (original ordinate)	19.623	2.41	20
K_{\min} (slope)	0.00730	0.0087	0
$K_0 - K_{\min}$ (original ordinate)	6.558	8.55	2
$K_0 - K_{\min}$ (slope)	423.065	15.38	424
$K_0 - K_{\min}$ (exponential coefficient)	0.001498	0.0012	0.001472

Table 2. Results of the estimates averaged over the 30 datasets simulated from estimates based on the EURO database.

Choice of functionals

	linear		shifted exponential
α	$\mathbf{K}_{\min}(\mathbf{T}) = a_1 + a_2 \cdot T$	$\mathbf{K}_0(\mathbf{T}) - \mathbf{K}_{\min}(\mathbf{T}) = b_1 + b_2 \exp(b_3 \cdot T)$	
4.18 (0.19)	$a_1 = 20.55$ (3.12)	$b_1 = 52.90$ (8.4)	
	$a_2 = 0.015$ (0.024)	$b_2 = 196.21$ (11.6)	
		$b_3 = 0.0203$ (0.003)	
	shifted exponential		shifted exponential
α	$\mathbf{K}_{\min}(\mathbf{T}) = a_1 + a_2 \exp(a_3 \cdot T)$	$\mathbf{K}_0(\mathbf{T}) - \mathbf{K}_{\min}(\mathbf{T}) = b_1 + b_2 \exp(b_3 \cdot T)$	
4.22 (0.28)	$a_1 = 14.20$ (6.37)	$b_1 = 53.26$ (9.67)	
	$a_2 = 11.68$ (11.84)	$b_2 = 186.56$ (13.58)	
	$a_3 = 0.0540$ (0.04)	$b_3 = 0.0188$ (0.0024)	

Table 3. Average estimation results (standard deviation within parentheses) for the Master Curve model for simulated datasets.

Model indic.	K_{\min}	α	$K_0 - K_{\min}$	transition temp. T_0	AIC	χ^2 test $p - value$	Figure (SOM)
MC	fixed (20)	fixed (4)	shifted exponential	-97.393°C	3545.93	1.10^{-6}	MC-1
1	linear	linear	linear	-99.99°C	3567	1.10^{-6}	S-1
2	linear	linear	quadratic	-86.47°C	3414	0.0043	S-3
3	linear	linear	shifted exponential	-91.43°C	3413	0.222	S-5
4	quadratic	linear	linear	-99.99°C	3462	1.10^{-6}	S-7
5	quadratic	linear	quadratic	-93.05°C	3410	0.0914	S-9
6	quadratic	linear	shifted exponential	-89.74°C	3414	0.4638	S-11
7	shifted exponential	linear	linear	-99.99°C	3544	1.10^{-6}	S-13
8	shifted exponential	linear	quadratic	-88.69°C	3388	0.0305	S-15
9	shifted exponential	linear	shifted exponential	-90.65°C	3414	0.4859	S-17
10	linear	constant	linear	-99.99°C	3613	1.10^{-6}	S-19
11	linear	constant	quadratic	-90.58°C	3420	0.232	S-21
12	linear	constant	shifted exponential	-89°C	3415	0.5751	S-23
13	quadratic	constant	linear	-99.99°C	3603	1.10^{-6}	S-25
14	quadratic	constant	shifted exponential	-91.04°C	3412	0.5975	S-27
15	shifted exponential	constant	linear	-99.99°C	3595	1.10^{-6}	S-29
16	shifted exponential	constant	quadratic	-88.70°C	3428	0.1438	S-31
17	shifted exponential	constant	shifted exponential	-89.91°C	3412	0.4328	S-33

Table 4. Model comparisons for the EURO database (valid toughness data only). Figures MC-1 and S-*i* refer to figures presented within the Supplementary Online Material (SOM) that accompanies this article. MC is for the usual Master Curve.

TABLES

Model indic.	K_{\min}	α	$K_0 - K_{\min}$	transition temp. T_0	AIC	χ^2 test $p - value$	Figure (SOM)
1	linear	linear	linear	-99.99°C	3601	1.10^{-6}	S-2
2	linear	linear	quadratic	-86.26°C	3461	0.0044	S-4
3	linear	linear	shifted exponential	-89.17°C	3460	0.687	S-6
4	quadratic	linear	linear	-99.99°C	3579	1.10^{-6}	S-8
5	quadratic	linear	quadratic	-86.14°C	3447	0.0615	S-10
6	quadratic	linear	shifted exponential	-92.65°C	3461	0.4351	S-12
7	shifted exponential	linear	linear	-99.99°C	3579	1.10^{-6}	S-14
8	shifted exponential	linear	quadratic	-89.26°C	3467	0.0164	S-16
9	shifted exponential	linear	shifted exponential	-91.03°C	3466	0.3945	S-18
10	linear	constant	linear	-99.99°C	3651	1.10^{-6}	S-20
11	linear	constant	quadratic	-93.61°C	3460	0.0565	S-22
12	linear	constant	shifted exponential	-90.4°C	3466	0.85	S-24
13	quadratic	constant	linear	-99.99°C	3711	1.10^{-6}	S-26
14	quadratic	constant	shifted exponential	-91.52°C	3461	0.7191	S-28
15	shifted exponential	constant	linear	-99.99°C	3685	1.10^{-6}	S-30
16	shifted exponential	constant	quadratic	-86.57°C	3523	0.0708	S-32
17	shifted exponential	constant	shifted exponential	-91.63°C	3461	0.8113	S-34

Table 5. Model comparisons for the EURO database (all toughness data). Figures S- X refer to figures presented within the Supplementary Online Material (SOM) that accompanies this article. The χ^2 tests are conducted only by confronting assessed models with the uncensored empirical distribution.