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An info-gap framework for robustness assessment of epistemic uncertainty models in hybrid structural reliability analysis

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Abstract

The main objective of this work is to study the impact of the choice of input uncertainty models on robustness evaluations for probabilities of failure. Aleatory and epistemic uncertainties are jointly propagated by considering hybrid models and applying random set theory. The notion of horizon of uncertainty found in the info-gap method, which is usually used to assess the robustness of a model to uncertainty, allows to compare the bounds on the probability of failure obtained from different epistemic uncertainty models at increasing levels of uncertainty. Info-gap robustness and opportuneness curves are obtained and compared for the interval model, the triangular and trapezoidal possibility distributions, the probabilistic uniform distribution and the parallelepiped convex model on two academic examples and one industrial use-case. A specific demand value, as introduced in the info-gap method, is used as a value of information metric to quantify the gain of information on the probability of failure between less informative uncertainty models and a more informative ones.

Keywords: hybrid structural reliability, epistemic uncertainty, robustness, info-gap, random sets

1. Introduction

Structural reliability [1] is of particular interest for risk-sensitive industrial applications such as power generation [2] where system performance,

4 and therefore safety, is subject to uncertainty. In this context, the safety is
5 assessed by estimating reliability-oriented quantities of interest such as a low
6 probability of failure or a high-order quantile on a specific output variable
7 of interest. Two types of uncertainty are commonly distinguished, namely
8 aleatory and epistemic [3]. Aleatory uncertainty is associated to natural ran-
9 domness while epistemic uncertainty is understood as ignorance due to a
10 lack of knowledge and is therefore potentially reducible. High-risk systems
11 models are typical cases where epistemic uncertainty can be found as they
12 often represent events that are rarely or never encountered. However, the
13 potential impact of lack of knowledge must still be accounted for in order to
14 make an informed decision on the safety of the system.

15 The notion of robustness has many interpretations and mathematical
16 representations [4]. It is defined in this paper as the capacity of the system
17 to fulfill a criterion despite differences between its predicted and operational
18 behaviors which is a key point in engineering and more specifically in safety
19 assessment. The info-gap framework [5] proposes a metric that quantifies
20 the robustness of a possible decision to epistemic uncertainty by calculating
21 its worst performance at increasing levels of uncertainty in order to privilege
22 tolerance to unexpected situations over performance at a poor estimate of
23 the system's environment [6]. Info-gap may be applied in a wide range of
24 fields where decisions under severe uncertainty need to be made such as
25 in structural design under seismic loads [7], climate policies [8] or water
26 resource planning [9]. Its application to reliability quantities of interest such
27 as probabilities of failure has been studied less. One example concerning
28 the reliability of penstocks can be found in [10] where epistemic uncertainty
29 affects physical variables and input distribution parameters which can be
30 seen as a parametric probability box problem.

31 While aleatory uncertainty is systematically treated using the probabilis-
32 tic framework, many different, yet potentially related, representations are
33 used to deal with epistemic uncertainty. If the info-gap framework chooses
34 to use convex models of uncertainty [11], other representations such as in-
35 terval model (which is a special case of convex models), Dempster-Shafer
36 structures [12], possibility distributions [13] or probability boxes [14] are also
37 common. Beer et al. [15] and Zio and Pedroni [16] propose reviews for such
38 methods. In many applications, both types of uncertainty coexist. There-
39 fore, the standard reliability analysis for which only aleatory uncertainty is
40 modeled must be transformed to hybrid reliability analysis (HRA). A gener-
41 alized framework is thus required to estimate hybrid reliability quantities of

42 interest. Random set (RS) theory [17] provides such framework as it enables
43 to represent and propagate combined uncertainty representations in order to
44 estimate, for example, the bounds on the probability of failure.

45 A robustness analysis depends on how the epistemic uncertainty is mod-
46 eled. Two different convex models may lead to different values of probabilities
47 of failure which in turn leads to the following question: to what extent does
48 the choice of the epistemic uncertainty representation affect a robustness
49 analysis? In this paper, in the context of HRA, a methodology is proposed
50 to assess, within the info-gap framework, the robustness of small probabilities
51 of failure with respect to the choice of a specific representation of epistemic
52 uncertainty in the inputs. To do so, several epistemic uncertainty models are
53 considered using RS theory. This methodology enables to compare info-gap
54 metrics - the so-called robustness and opportuneness curves and a value of
55 information metric defined as the demand value - obtained from different
56 uncertainty representations but also to highlight their implicit relationships.

57 The paper is organized as follows: Section 2 reviews the formulation of a
58 HRA with the use of RS theory and ends with the main aspects of an info-gap
59 analysis; Section 3 describes the framework that is used and how info-gap and
60 RS theory are combined to compare uncertainty representations; Section 4
61 shows the results of the methodology applied to two academic examples and
62 one industrial use-case that concerns the structural reliability of penstocks;
63 finally Section 5 proposes some discussions about the presented work before
64 concluding it in Section 6.

65 **2. Hybrid reliability analysis**

66 *2.1. List of common epistemic uncertainty representations*

67 The probabilistic framework is a very powerful and detailed way to model
68 and propagate aleatory uncertainty. Appendix A briefly recalls how such
69 framework may be used for standard reliability analysis and more specifically
70 for estimating a probability of failure. Nevertheless, the exact knowledge of
71 the joint probability density function (pdf) $f_{\mathbf{X}}$ requires the knowledge of
72 the marginal pdf of each component X_i and the dependence structure (i.e.,
73 the copula) between components which is often not known especially when
74 only limited data is available. Epistemic uncertainty characterizes the lack
75 of information as it is potentially reducible by gathering more knowledge.

76 As mentioned in the introduction, many types of epistemic models can be
77 found in the literature depending on the nature of the uncertainty and the

78 available information. The main properties of the uncertainty representations
 79 investigated in this paper, namely interval model, convex model, evidence
 80 theory, possibility distributions and probability box (p-box) theory, are given
 81 in Appendix B and may be further investigated by the reader with the
 82 corresponding references. In order to maintain a coherence in the rest of the
 83 paper, the variables that are modeled by such representations are described
 84 by the vector $\mathbf{Y} = (Y_1, Y_2, \dots, Y_{n_Y})^\top$.

85 *Links between the different uncertainty models mentioned above.* Fig. 1 sum-
 86 marizes the main links between the different uncertainty representations
 87 when considering structural reliability where each number has the follow-
 88 ing meaning:

- 89 1. Adds the information of dependency with a convex model and its co-
 90 efficient of correlation;
- 91 2. Assigns weights to subsets of the interval with the mass distribution ν ;
- 92 3. Assigns a possibility distribution $\pi(\cdot)$ in the interval;
- 93 4. $Y^L = Y^U$;
- 94 5. Adds the information of the probability law;
- 95 6. $\bar{F}_Y = \underline{F}_Y$;
- 96 7. $\bar{F}_Y = \text{Pl}(Y \leq y)$ and $\underline{F}_Y = \text{Bel}(Y \leq y)$ (see [18] for more information);
- 97 8. Discretizes the support of the distribution into disjoint intervals of
 98 weight $\nu([y_i, y_{i+1}]) = \nu_i = \text{Pr}(Y \in [y_i, y_{i+1}])$ (see [18] for more infor-
 99 mation);
- 100 9. $\bar{F}_Y = \text{N}(Y \leq y)$ and $\underline{F}_Y = \text{II}(Y \leq y)$ (see [18] for more information);
- 101 10. Discretizes the possibility distribution into nested intervals by equally
 102 discretizing the α -axis and assign the weight $\nu_i = \alpha_i - \alpha_{i+1}$ to the
 103 corresponding interval $[\underline{y}_i, \bar{y}_i]$ which is the α_i -cut (see [18] for more
 104 information).

105 The figure can be read from top to bottom in terms of added informa-
 106 tion and a solid line represents the path from a less informative model to a
 107 more informative one. The dotted lines represent a path from a model to
 108 another without adding information. Note that a solid line could be added
 109 from the interval to the probability boxes but has been removed here to make
 110 the diagram easier to read. The comparison in terms of degree of informa-
 111 tion cannot be made in the proposed context between two models with no
 112 solid line joining them. For example, a convex model and the free p-box

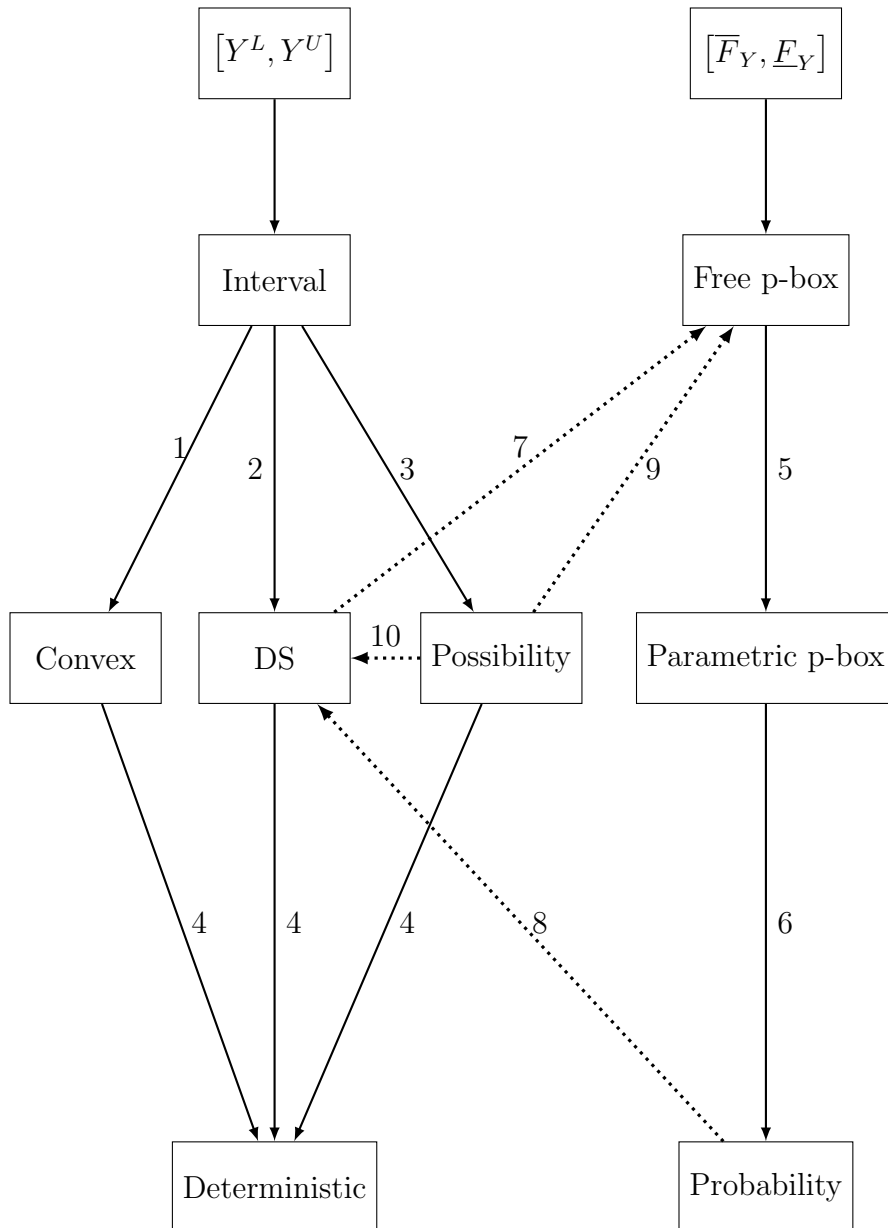


Figure 1: Diagram of various uncertainty representations.

113 representation are not directly comparable. Two groups of models may be
 114 distinguished in the diagram. On the left side, the uncertainty representa-
 115 tions are interval-based. If no information is added to the bounds of the

116 epistemic variables, the interval model and more generally the convex model
 117 may be used. DS structures and possibility distributions enable to divide the
 118 initial interval into more or less plausible smaller intervals based on expert
 119 knowledge. These representations reduce to a deterministic value with no
 120 epistemic uncertainty. On the right side, the uncertainty representations are
 121 probability-based. The path of information goes from the free to the para-
 122 metric p-box representations and finally reduces to the purely probabilistic
 123 representation. Although these two groups of models seem to be built on
 124 different theoretical frameworks, the dotted lines show how they may be re-
 125 lated in the context of reliability. Indeed, the following section explains how
 126 these models may be modeled in a common framework.

127 *2.2. Hybrid reliability analysis using random set theory*

This work falls in the scope of HRA, meaning that the input vector can be divided into two vectors, namely \mathbf{X} and \mathbf{Y} where \mathbf{X} is a random vector with a fully determined pdf $f_{\mathbf{X}}$ and \mathbf{Y} contains the input variables subject to epistemic uncertainty and described by one of the models mentioned previously. For a given realization of the random vector \mathbf{X} , the hybrid limit-state function $g(\mathbf{X}, \mathbf{Y})$ is also a random set. As such, it is not possible to compute a single probability of failure as in standard reliability analysis but only its bounds denoted by $[\underline{P}_f, \overline{P}_f]$ where:

$$\underline{P}_f = \Pr [\overline{g}(\mathbf{X}, \mathbf{Y})] = \Pr [\max g(\mathbf{X}, \mathbf{Y}) \leq 0] \quad (1a)$$

$$\overline{P}_f = \Pr [\underline{g}(\mathbf{X}, \mathbf{Y})] = \Pr [\min g(\mathbf{X}, \mathbf{Y}) \leq 0]. \quad (1b)$$

128 In order to apply the existing probability of failure estimation methods
 129 to the hybrid problem, a framework that enables the propagation of random
 130 variables with a mixture of different epistemic models is needed. RS theory
 131 makes it possible [19, 20] as it generalizes probabilistic and epistemic models.
 132 A random set is very closely related to evidence theory and is defined by the
 133 function Γ :

$$\Gamma : \left\{ \begin{array}{l} \Omega \longrightarrow A \\ \boldsymbol{\alpha} \longrightarrow \Gamma(\boldsymbol{\alpha}) \end{array} \right. \quad (2)$$

where A is the focal set and $\Gamma(\boldsymbol{\alpha})$ is a focal element. In other words, a random set is similar to a random variable whose realization is a set in A , not a scalar. The event E is bounded by an upper probability and a lower

probability that are quite similar to Eqs. (6.a) and (6.b):

$$\underline{P}_\Gamma(E) = P_\Omega(\{\boldsymbol{\alpha} \in \Omega : \Gamma(\boldsymbol{\alpha}) \subseteq E, \Gamma(\boldsymbol{\alpha}) \neq \emptyset\}) \quad (3a)$$

$$\overline{P}_\Gamma(E) = P_\Omega(\{\boldsymbol{\alpha} \in \Omega : \Gamma(\boldsymbol{\alpha}) \cap E \neq \emptyset\}) \quad (3b)$$

134 with $P_\Gamma := P_\Omega \circ \Gamma^{-1}$. This definition links RS with the different uncertainty
 135 representations mentioned before as presented in Table 1 which gives the
 corresponding RS for each uncertainty representation.

Table 1: The expression of $\Gamma_{Y_i}(\alpha)$ for each uncertainty representation.

| Uncertainty model | $\Gamma_{Y_i}(\alpha)$ |
|-------------------|-----------------------------------------------------------------------|
| Interval | I_{Y_i} |
| Convex | $C(I_Y, \boldsymbol{\rho})$ |
| Possibility | $\{y \in Y_i : \pi_{Y_i}(y) \geq \alpha\}$ |
| Free p-box | $[\overline{F}_{Y_i}^{-1}(\alpha), \underline{F}_{Y_i}^{-1}(\alpha)]$ |
| Probability | $F_{Y_i}^{-1}(\alpha)$ |

136

A RS can also be obtained from evidence theory by relating it to the p-box representation as shown in Fig. 1. The interval and convex models are special cases where the RS is actually a constant set as the function does not depend on $\boldsymbol{\alpha}$. The probability model is a special case where the random set is a singleton. A sample of the random set in higher dimension than one is obtained by sampling the vector $\boldsymbol{\alpha}$ from a copula C and computing the Cartesian product $\times_{k=1}^{n_\alpha} \Gamma_k(\alpha_k)$ which is a n_α -box with $n_\alpha = n_X + n_Y$ being the number of input variables. The limit-state functions in Eqs. (11.a) and (11.b) can be rewritten as follows:

$$\overline{g}(\mathbf{X}, \mathbf{Y}) = \overline{g}(\boldsymbol{\alpha}) = \max_{\Gamma_{(X,Y)}(\boldsymbol{\alpha})} g(\boldsymbol{\alpha}) \quad (4a)$$

$$\underline{g}(\mathbf{X}, \mathbf{Y}) = \underline{g}(\boldsymbol{\alpha}) = \min_{\Gamma_{(X,Y)}(\boldsymbol{\alpha})} g(\boldsymbol{\alpha}) \quad (4b)$$

which yields for the bounds on P_f :

$$\overline{P}_f = \int_{\Omega} \mathbb{1}_{\underline{g}(\boldsymbol{\alpha}) \leq 0} dC(\boldsymbol{\alpha}) \quad (5a)$$

$$\underline{P}_f = \int_{\Omega} \mathbb{1}_{\overline{g}(\boldsymbol{\alpha}) \leq 0} dC(\boldsymbol{\alpha}). \quad (5b)$$

The HRA problem thus reduces to two standard reliability analyses for which standard estimation methods may be used. It is important to notice, as pointed out in [21], that when considering only interval or parametric p-box models on \mathbf{Y} , the bounds obtained using the RS framework are larger than the ones obtained by applying a straightforward search for the maximum and minimum of the probability of failure in the interval domain (on the physical variables or the distributional parameters). For example, with the interval model, the following equations hold:

$$\Pr \left[\max_{\Gamma_{(X,Y)}(\boldsymbol{\alpha})} g(\boldsymbol{\alpha}) \leq 0 \right] \leq \min_{D_Y} \Pr [g(\mathbf{X}, \mathbf{Y}) \leq 0] \quad (6a)$$

$$\Pr \left[\min_{\Gamma_{(X,Y)}(\boldsymbol{\alpha})} g(\boldsymbol{\alpha}) \leq 0 \right] \geq \max_{D_Y} \Pr [g(\mathbf{X}, \mathbf{Y}) \leq 0]. \quad (6b)$$

137 When estimating the bounds of the probabilities of failure when considering
 138 the interval or distributional p-box models in the following application cases,
 139 the results obtained by applying RS theory will be compared with those
 140 obtained by performing a global optimization on the probability of failure
 141 using DIRECT algorithm [22].

142 2.3. Robustness analysis

143 Robustness analysis is of particular interest in engineering applications.
 144 A system is considered robust if small variations on an expected state of op-
 145 eration do not considerably deteriorate the expected performance. A robust
 146 solution may be preferable over a non-robust optimal solution [6]. The info-
 147 gap framework aims at quantitatively measuring this notion of robustness
 148 in the context of decision making by introducing the following robustness
 149 function h_{IG}^* given by:

$$h_{\text{IG}}^* = \max_h \left\{ \max_{\mathbf{u} \in U(h, \tilde{\mathbf{u}})} R(\mathbf{q}, \mathbf{u}) \leq r_c \right\} \quad (7)$$

150 where h_{IG}^* is defined as the maximum amount of uncertainty that can be
 151 tolerated, i.e., for which the worst possible performance is still acceptable.
 152 Three components appear in the info-gap robustness function in Eq. (7):

- 153 • the performance function $R(\mathbf{q}, \mathbf{u})$ that evaluates the quantity of in-
 154 terest of a system of characteristic vector \mathbf{q} at specific values of the
 155 uncertain vector \mathbf{u} ;

- 156 • the critical performance r_c which is the value that the quantity of inter-
157 est must not exceed (to be distinguished with the threshold z_{th} intro-
158 duced in Eq. (A.1)). Its value may be determined or not in an info-gap
159 analysis;
- 160 • the uncertainty model $U(h, \tilde{\mathbf{u}})$ which is usually a non-probabilistic
161 convex set, as introduced in Section 2.2, of horizon of uncertainty
162 $h \in \mathbb{R}^+$ containing the best estimation $\tilde{\mathbf{u}}$ (nominal value of \mathbf{u}) of the
163 uncertain vector \mathbf{u} . For $h = 0$, $U(h, \tilde{\mathbf{u}})$ reduces to $\tilde{\mathbf{u}}$.

164 A key feature of the convex uncertainty models is that they are nested as the
165 illustrative example depicted in Fig. 2:

$$U(h_1, \tilde{\mathbf{u}}) \subseteq U(h_2, \tilde{\mathbf{u}}) \text{ for } h_1 \leq h_2. \quad (8)$$

166 Therefore, the robustness function is monotonous with respect to the horizon
167 of uncertainty and to the performance level.

168 Uncertainty can also be beneficial as the real performance of the system
169 may be better than the expected one. To illustrate this point, the oppor-
170 tuneness function β_{IG}^* is defined as:

$$\beta_{\text{IG}}^* = \min_h \left\{ \min_{\mathbf{u} \in U(h, \tilde{\mathbf{u}})} R(\mathbf{q}, \mathbf{u}) \leq r_w \right\} \quad (9)$$

171 where r_w can be seen as a reward threshold. The idea with the IG framework
172 is to compare the robustness values of different possible decisions \mathbf{d} in order
173 to retain the most robust one for a given critical performance value. The
174 most robust decision may depend on the choice of the critical performance
175 value as seen in Fig. 2 (right) where both curves cross each others. The
176 decision d_2 is more robust before the curves intersect but the decision d_1 is
177 more robust after. This crossing of robustness curves is called the *preference*
178 *reversal*. Few hypotheses are required in an IG analysis as it can be conducted
179 only with the choice of a non-probabilistic convex uncertainty model and the
180 best guess of the uncertain vector \mathbf{u} , e.g., its nominal value. However, both
181 hypotheses may have an influence on the robustness evaluation. The effect
182 of the uncertainty model on the robustness curve can be seen as a value
183 of information (VoI) analysis [23] where the aim is to quantify the gain in
184 robustness when using a more informative uncertainty model than another

185 one. An IG uncertainty model U_1 is more informative than U_2 if the following
 186 set inclusion is obtained:

$$U_1(h, \tilde{\mathbf{u}}) \subset U_2(h, \tilde{\mathbf{u}}), \forall h \geq 0. \quad (10)$$

187 For a given critical performance r_c , U_1 will yield a higher robustness value.
 188 For a given horizon of uncertainty, the worst performance in U_1 will be better
 189 than the one in U_2 . These comparisons are expressed respectively as the
 190 robustness premium Δh^* and the demand value Δr_c .

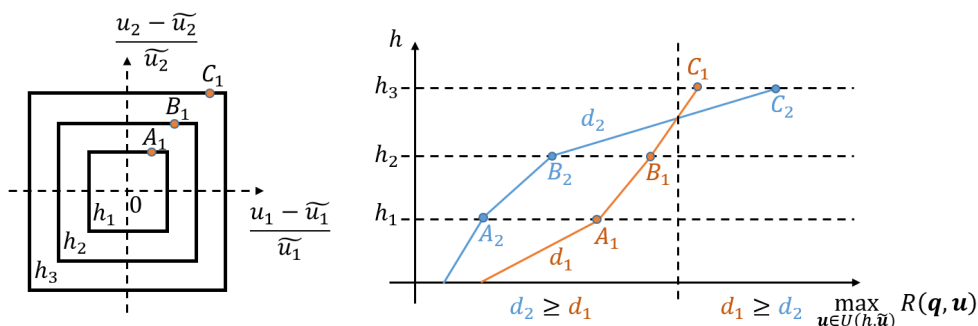


Figure 2: Nested convex sets (left) and associated robustness curves with preference reversal (right).

191 3. A new framework for assessing robustness in hybrid reliability 192 analysis

193 3.1. HRA framework

194 The goal in this work is to analyse the effect of the choice of an epistemic
 195 uncertainty model on the robustness of a reliability quantity of interest. Here,
 196 one considers the bounds of the probability of failure obtained by HRA as the
 197 two quantities of interest. As mentioned in Section 2, the limit-state function
 198 $g(\mathbf{X}, \mathbf{Y})$ depends on both vectors \mathbf{X} and \mathbf{Y} . The vector \mathbf{X} contains the input
 199 variables X_i that are modeled as random variables. The joint distribution
 200 $f_{\mathbf{X}}(\mathbf{x})$ is considered perfectly determined (no epistemic uncertainty). The
 201 vector \mathbf{Y} contains the input variables Y_i for which epistemic uncertainty
 202 does not allow a well defined deterministic or probabilistic modeling. As
 203 it was seen in Section 2, RS theory enables to model and propagate many
 204 different uncertainty models together (including probabilized inputs). In

205 order to compare the effect of each epistemic uncertainty model, the bounds
206 on the probability of failure are estimated and compared for a same epistemic
207 representation of each input variable Y_i . The different epistemic models for
208 which results are shown in this paper are:

- 209 • interval model;
- 210 • parallelepiped convex model;
- 211 • possibility triangular distribution;
- 212 • possibility trapezoidal distribution;
- 213 • DS structures;
- 214 • free and parametric p-boxes.

215 Probabilistic uniform distributions on Y_i are also added to the compar-
216 ison. In order to estimate the bounds on the probability of failure, Eqs.
217 (15.a) and (15.b) need to be evaluated. The inner loop which corresponds
218 to the search of the minimum and maximum of the limit-state function for
219 one realization of the random set $\Gamma(\boldsymbol{\alpha})$ may be performed using an opti-
220 mization algorithm. The outer loop corresponds to the estimation method
221 of the probability of failure. As an inner optimization loop is involved, HRA
222 usually requires more evaluations of the limit-state function than a standard
223 reliability analysis. Moreover, the lower bound of the probability of failure
224 to be estimated may be very small (e.g., such that $P_f < 10^{-5}$). Therefore,
225 some estimation methods such as crude Monte Carlo sampling may not be
226 practicable. In this paper, the outer loop is mainly performed with an Im-
227 portance Sampling around the most probable failure point obtained with a
228 FORM analysis [24]. The Subset Simulation algorithm [25] is also used in or-
229 der to verify the results. However, note that several other advanced sampling
230 methods could have been used here (e.g., directional sampling, line sampling)
231 [26].

232 3.2. Comparison by means of info-gap robustness and opportuneness curves

233 As seen in Section 2.3, the IG framework quantifies the notions of ro-
234 bustness and opportuneness to uncertainty by building nested convex sets
235 around a nominal state which represents the analyst's best guess. An in-
236 teresting feature is that it enables to compare different possible decisions

237 in view of choosing the one that maximizes the robustness given a critical
 238 performance. IG analysis can also be used to assess the VoI induced by a
 239 more informative input model. Indeed, the different decisions can be directly
 240 linked to the choice of different uncertainty models $U_i(h, \tilde{\mathbf{u}})$ that each has its
 241 own degree of information. Therefore, it is possible to compare robustness
 242 and opportuneness curves of different uncertainty models for \mathbf{Y} by consider-
 243 ing the random set function Γ_i as the info-gap uncertainty model as follows:

$$U_i(h, \tilde{\mathbf{Y}}) = \Gamma_i(\alpha, h) \quad (11)$$

244 with:

$$\Gamma_i : \begin{cases} [0, 1]^{n_Y} \times \mathbb{R}^+ & \longrightarrow \text{Supp}_{\mathbf{Y}}(h, \tilde{\mathbf{Y}}) \\ (\alpha, h) & \longrightarrow \Gamma_i(\alpha, h) \end{cases} \quad (12)$$

245 where $[0, 1]^{n_Y}$ is the unit hypercube and $\text{Supp}_{\mathbf{Y}}$ is the support of \mathbf{Y} that gets
 246 wider when the horizon of uncertainty h increases:

$$\text{Supp}_{\mathbf{Y}}(h, \tilde{\mathbf{Y}}) = \left\{ \mathbf{Y} : \tilde{\mathbf{Y}}(1 - h) \leq \mathbf{Y} \leq \tilde{\mathbf{Y}}(1 + h) \right\}, h \geq 0. \quad (13)$$

247 The robustness function in Eq. (7) translates with the proposed method-
 248 ology to:

$$h_{\text{IG}}^* = \max_h \{ \bar{P}_f(\Gamma_i) \leq P_f^{\text{cr}} \} \quad (14)$$

249 where P_f^{cr} is the critical probability of failure that may or may not be known.
 250 In practice, instead of searching for h_{IG}^* , the robustness curve can be plotted
 251 by estimating \bar{P}_f for a certain number n_h of horizons of uncertainty that
 252 belong to a chosen interval $h_j \in [0, h_{\text{max}}]$, $j = 1, \dots, n_h$. The same method
 253 can be applied to plot the opportuneness curve by estimating several times
 254 \underline{P}_f . Note that in Eq. (12) the random set function is only applied on \mathbf{Y} for
 255 the sake of conciseness. In the application cases, the random set function
 256 also takes into account the random variable \mathbf{X} as in Eqs. (14.a) and (14.b).

257 Whatever the type of uncertainty model that is used for \mathbf{Y} , for a given
 258 level of horizon of uncertainty h , the same support is used to compare bounds
 259 obtained from each model which enables a meaningful comparison. Moreover,
 260 the fact that bounds are calculated for increasing horizons of uncertainty and,
 261 therefore, growing supports, enables a comparison in terms of robustness
 262 (upper bound \bar{P}_f) and opportuneness (lower bound \underline{P}_f) functions. The larger
 263 the support, the more impact the choice of the uncertainty model has on the
 264 bounds of the probability of failure. The following quantity $R_{\bar{P}_f}^{(ij)}$ is defined

265 in this paper as the demand value between a less informative uncertainty
 266 model U_i and a more informative uncertainty model U_j and is used as the
 267 Vol metric:

$$R_{\overline{P}_f}^{(ij)} = 1 - \frac{\overline{P}_f(\Gamma_i(\boldsymbol{\alpha}, h))}{\overline{P}_f(\Gamma_j(\boldsymbol{\alpha}, h))} \quad (15)$$

268 The value of this metric, which is negative as $\overline{P}_f(\Gamma_i(h)) \geq \overline{P}_f(\Gamma_j(h))$, shows
 269 how the added information from model U_i to model U_j diminishes, in terms
 270 of percentage, the upper bound of the probability of failure. A similar metric
 271 could be defined with the lower bound to quantify how a more informative
 272 model reduces the best possible outcome. This last metric is not used in
 273 this paper since, in the context of a reliability analysis, the main concern is
 274 to understand how the worst possible outcome may be reduced with more
 275 information.

276 3.3. Sensitivity to the gain of information

277 The field of sensitivity analysis has a very large background which is not
 278 discussed in this paper as it is not the main topic [27]. Sensitivity analy-
 279 sis aims at identifying the variables that have a significant impact on the
 280 quantity of interest in order to simplify the numerical model or to help the
 281 analyst decide where to judiciously allocate resources [28]. Many metrics
 282 exist depending on the analyst's objective. In this paper, a simple metric is
 283 defined in order to identify the epistemic variables where added information
 284 contributes the most to the global gain of information on the bounds of the
 285 probability of failure. The idea is then to compare the demand value $R_{\overline{P}_f}$ ob-
 286 tained by considering a more informative uncertainty representation on one
 287 variable at a time and compare it with the value obtained when considering
 288 all variables at once. The following metric is defined:

$$S_{Y_k}^{(ij)} = \frac{R_{\overline{P}_f}^{(ij)(k)}}{R_{\overline{P}_f}^{(ij)}}. \quad (16)$$

289 where:

$$R_{\overline{P}_f}^{(ij)(k)} = 1 - \frac{\overline{P}_f(\Gamma_i(\boldsymbol{\alpha}, h))}{\overline{P}_f(\Gamma_j^{(k)}(\boldsymbol{\alpha}, h))} \quad (17)$$

290 with $\Gamma_j^{(k)} = [\Gamma_i(\alpha_1, h), \dots, \Gamma_j(\alpha_k, h), \dots, \Gamma_i(\alpha_{n_Y}, h)]^\top$. This metric gives
 291 the contribution of information gained from an uncertainty model to a more

292 informative one brought by each variable. The metric depends on the hori-
 293 zon of uncertainty which means that a variable may be informative for some
 294 range of horizon of uncertainty and less informative for other values. This
 295 characteristic can contribute valuable knowledge to the decision-making pro-
 296 cess.

297 3.4. Proposed methodology

298 This section aims at summarizing the steps that are followed to apply the
 299 proposed methodology to three reliability problems. The different steps are
 300 presented in Fig. 3 where each box is detailed as follows:

- 301 1. Compute the limit-state function $g(\mathbf{X}, \mathbf{Y})$, build a comparison group
 302 \mathbf{G} that contains different uncertainty models M_i to be compared, define
 303 the values of the horizon of uncertainty h_j for which the bounds on the
 304 probability of failure will be estimated, associate the joint cumulative
 305 distribution function $F_{\mathbf{X}}(\mathbf{x})$ to \mathbf{X} and the nominal values $\tilde{\mathbf{Y}}$ to \mathbf{Y} ;
- 306 2. Get the random set function Γ_i that corresponds to the uncertainty
 307 model M_i as presented in Table 1;
- 308 3. Compute the support $\text{Supp}_{\mathbf{Y}}(h_j, \tilde{\mathbf{Y}})$ as defined in Eq. 13 which en-
 309 ables to compute the random set function $\Gamma_i(\boldsymbol{\alpha}, h_j)$ as defined in Eq.
 310 12;
- 311 4. For each discretized value h_j , estimate the bounds on the probability
 312 of failure where each random variable α_k follows the standard uniform
 313 distribution and each corresponding realization is either the maximum
 314 value of the limit-state function in $\Gamma_i(\boldsymbol{\alpha}, h_j)$ (estimation of \underline{P}_f) or the
 315 minimum value (estimation of \overline{P}_f) obtained with an optimization al-
 316 gorithm. The privileged method used to estimate the probabilities is
 317 FORM-IS but SS is also used as a verification method. More details
 318 on the optimization and probabilities estimation algorithms are given
 319 in Section 4.1;
- 320 5. Once the bounds on the probability of failure are obtained for each
 321 discretized horizon of uncertainty h_j and for each uncertainty model
 322 M_i , the VoI metric $R_{\overline{P}_f}$, as defined in Eq. 15, is evaluated;
- 323 6. Show the robustness (\overline{P}_f) and opportuneness (\underline{P}_f) curves obtained with
 324 each uncertainty model M_i and show the surface plot $R_{\overline{P}_f}(h)$ which
 325 is a function of h and the two different uncertainty models that are
 326 compared in terms of information;

327 Note that the sensitivity analysis is not present in Fig. 3. The only addition
 328 is the estimation of $\overline{P}_f \left(\Gamma_j^{(k)}(\boldsymbol{\alpha}, h) \right)$ in Eq. 17 which requires to consider the
 329 more informative model M_j on one variable Y_k at a time and compute $S_{Y_k}^{(ij)}$
 330 as defined in Eq. 16.

331 4. Applications

332 4.1. Test cases and numerical tools used

333 The methodology that is proposed throughout this paper is applied on
 334 two academic examples, or toy-cases, and one industrial case which is rel-
 335 evant to the French electricity supplier EDF. The two academic examples
 336 correspond to modified versions of the three-dimensional Rosenbrock func-
 337 tion and a two-degree-of-freedom oscillator system. The main objective is
 338 to compare robustness and opportuneness curves obtained from various un-
 339 certainty models with increasing level of informativeness. Therefore, the
 340 following groups of comparison are created:

- 341 • \mathbf{M}_1 : interval RS, interval DIRECT, trapezoidal possibility distribution,
 342 triangular possibility distribution, probabilistic uniform distribution;
- 343 • \mathbf{M}_2 : interval RS, parallelepiped convex model;
- 344 • \mathbf{M}_3 : free p-box, parametric p-box.

345 The group \mathbf{M}_1 corresponds to added information represented by the solid
 346 lines 3 and 4 in Fig. 1 and the solid line that could have been plotted
 347 between the interval and probability boxes. When considering the interval
 348 model, a distinction is made between “interval RS” which means that the
 349 bounds on the probability of failure are estimated using RS theory (left side
 350 of the inequalities in Eq. (16)) and “interval DIRECT” which means that the
 351 bounds are estimated by using the global optimization algorithm DIRECT
 352 directly on the probability of failure (right side of the inequalities in Eq.
 353 (16)). The group \mathbf{M}_2 corresponds to added information represented by the
 354 solid line 1. The group \mathbf{M}_3 corresponds to added information represented by
 355 the solid line 5.

356 Robustness and opportuneness curves are also presented in order to verify
 357 numerically the links between possibility distributions, DS theory, p-boxes
 358 and probability distributions. The following groups of comparison are defined
 359 for that purpose:

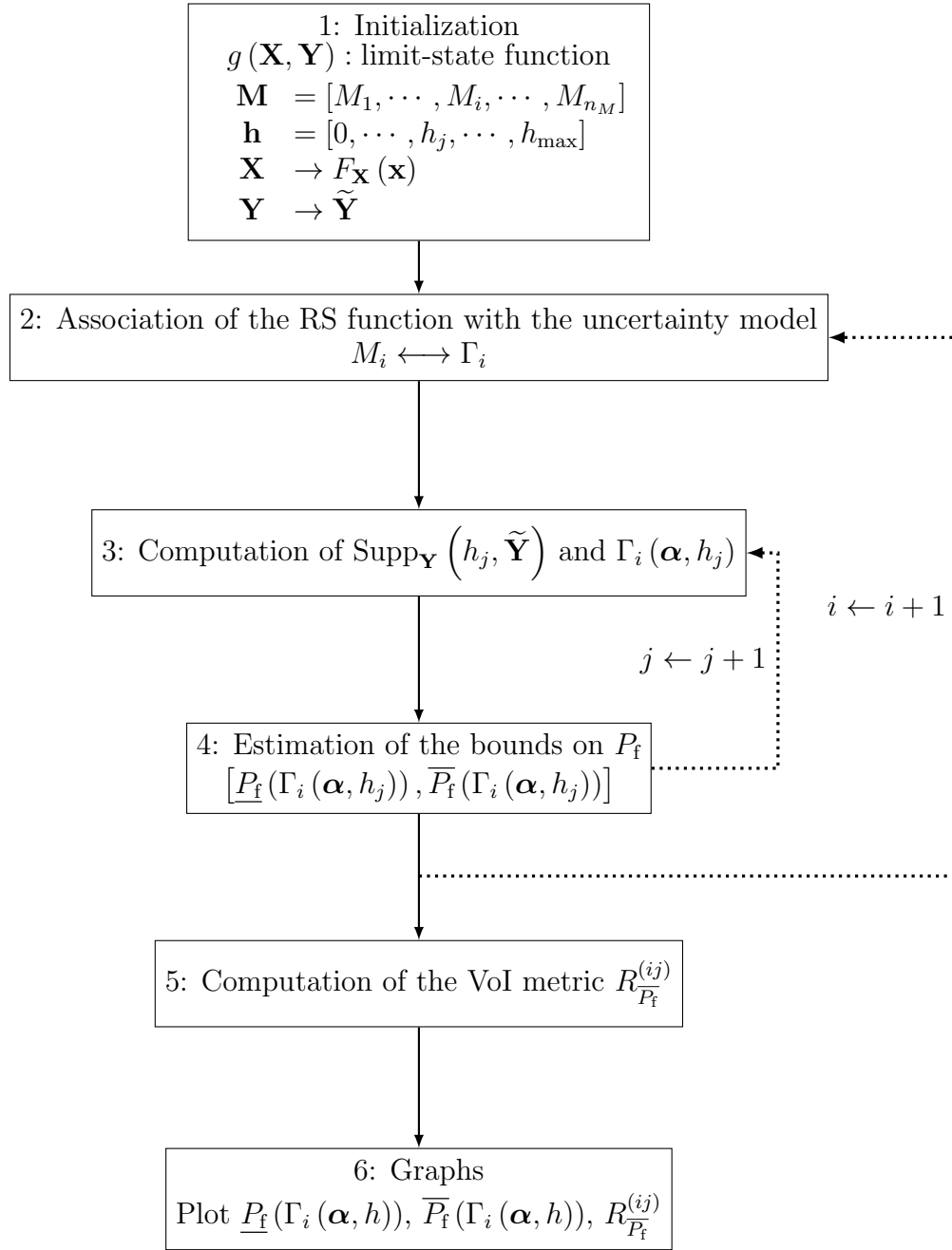


Figure 3: Workflow of the proposed methodology.

- 360 • \mathbf{M}_4 : triangular possibility distribution, DS structures, free p-box;
- 361 • \mathbf{M}_5 : DS structures, probabilistic uniform distribution.

362 The group \mathbf{M}_4 corresponds to the dotted lines 7, 9 and 10 in Fig. 1. The
 363 group \mathbf{M}_5 corresponds to the dotted line 8.

364 Parametric p-box results are also obtained using the DIRECT algorithm
 365 in the hyperrectangle resulting from each uncertain hyperparameter of the
 366 distribution law represented as a interval. For all the other models, the
 367 bounds are estimated using the RS framework. Moreover, hybrid limit-state
 368 functions are shown with the Rosenbrock function and the previously defined
 369 sensitivity and VoI metrics are computed. The methodology was numerically
 370 implemented with Python using mainly the Scipy package to solve the op-
 371 timization problems (scipy.optimize module) arising from the hybrid limit-
 372 state functions, and the OpenTURNS software [29] to estimate probabilities
 373 of failure using mainly FORM-IS but also Subset Simulation for verification.
 374 When available, the robustness and opportuneness curves are given with their
 375 corresponding 95% confidence interval (dotted lines).

376 4.2. Toy case 1: the Rosenbrock function

377 The first toy case has the following limit-state function based on Rosen-
 378 brock function in three dimensions:

$$g(\mathbf{X}, Y) = 100(Y - X_2^2)^2 + (X_2 - 1)^2 + 100(X_2 - X_1^2)^2 + (X_1 - 1)^2 - 3 \quad (18)$$

379 where X_1 and X_2 follow standard Gaussian distributions and Y is the only
 380 epistemic variable with a nominal value of $Y^C = 0.9$. Robustness and oppor-
 381 tuneness curves are obtained by estimating the bounds $[\underline{P}_f, \overline{P}_f]$ for $n_h = 15$
 382 horizon levels for $h \in [0, 0.19]$. As Y has a single component, the convex
 383 model reduces to the interval model. The groups of uncertainty models on
 384 which results are provided are \mathbf{M}_1 , \mathbf{M}_3 , \mathbf{M}_4 and \mathbf{M}_5 . The fact that the input
 385 dimension here is $n_\alpha = n_X + n_Y = 3$ enables to draw the iso-lines of both
 386 limit-state surfaces $\underline{g}(\boldsymbol{\alpha}, h) = 0$ and $\overline{g}(\boldsymbol{\alpha}, h) = 0$ in the $\boldsymbol{\alpha}$ -space for different
 387 values of h and different uncertainty models. Note that the $\boldsymbol{\alpha}$ -space is the
 388 unit hypercube of dimension $n_X + n_Y$ and that α_{X_i} represents the quantile
 389 order of X_i .

390 \mathbf{M}_1 results. The isolines of the limit-state functions for the interval model on
 391 Y are shown in Fig. 4, where the failure domain lies in the ellipsoid shape.
 392 Since, for a given h , Y is a unique interval, its corresponding random set is
 393 the same interval and does not depend on α_Y . Therefore, for a given h , the
 394 failure domain is a surface. The isolines are given at increasing horizons of
 395 uncertainty $h \in [0, 0.19]$ which is why the plot is three-dimensional. One can
 396 see how $\underline{g}(\boldsymbol{\alpha}, h) = 0$ (used for \overline{P}_f estimation) gradually expands with h while
 $\overline{g}(\boldsymbol{\alpha}, h) = 0$ (used for \underline{P}_f estimation) gradually reduces as expected.

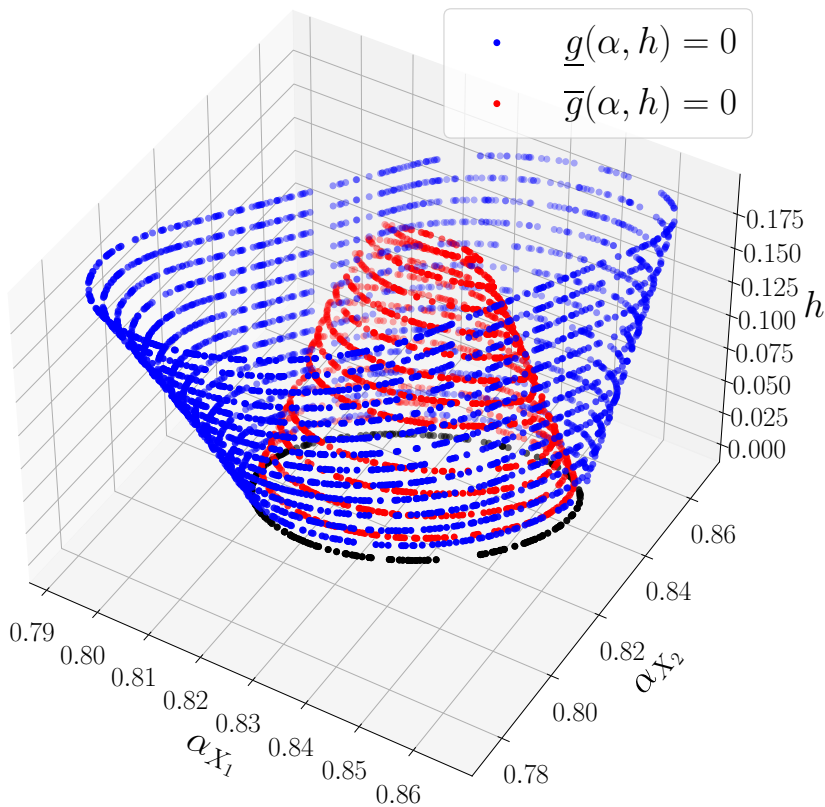


Figure 4: Illustration of limit-state surfaces $\underline{g}(\boldsymbol{\alpha}, h) = 0$ and $\overline{g}(\boldsymbol{\alpha}, h) = 0$ for the interval representation for the Rosenbrock function.

397
 398 Fig. 5 compares the isolines of the limit-state surfaces between the tri-
 399 angular and trapezoidal distributions at a given horizon level $h = 0.19$. In
 400 this case, the dimension of $\boldsymbol{\alpha}$ is 3 which means that the failure domain is

401 a volume which is why it is illustrated for a single value of h . For a given
 402 $\boldsymbol{\alpha}$, the corresponding random set induced by the triangular distribution is
 403 contained in the random set induced by the trapezoidal distribution. This
 404 explains why the failure volume obtained from the triangular model is contained
 405 in the one obtained from the trapezoidal model when considering the
 406 limit-state function $\underline{g}(\boldsymbol{\alpha}, h) = 0$ while the opposite happens when considering
 the limit-state function $\bar{g}(\boldsymbol{\alpha}, h) = 0$.

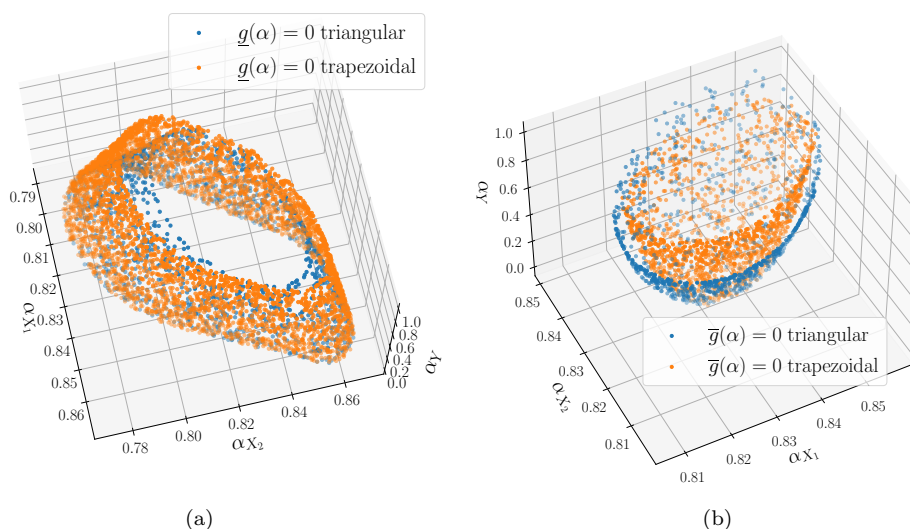


Figure 5: Comparison of $\underline{g}(\boldsymbol{\alpha}) = 0$ in (a) and $\bar{g}(\boldsymbol{\alpha}) = 0$ in (b) for the triangular and trapezoidal uncertainty models.

407 The analysis of the limit-state functions already gives a strong intuition
 408 on the inclusions of the bounds on the probability of failure obtained from
 409 the different uncertainty representations in \mathbf{M}_1 . Fig. 7.(a) presents the
 410 robustness and opportuneness curves for the four different uncertainty mod-
 411 els. The expected inclusions are obtained. One can notice that the extreme
 412 probabilities of failure remain close to the nominal result except for the lower
 413 probabilities of failure obtained with the interval model and considering RS
 414 theory (i.e., interval RS). This could be expected looking at Fig. 4 as the
 415 ellipses shrink considerably when the horizon of uncertainty grows. Never-
 416 theless, computing the results of the interval model using the optimization
 417 method (i.e., interval DIRECT) yields very different results as the bounds
 418 on the probability of failure become very tight, even tighter than the bounds
 419

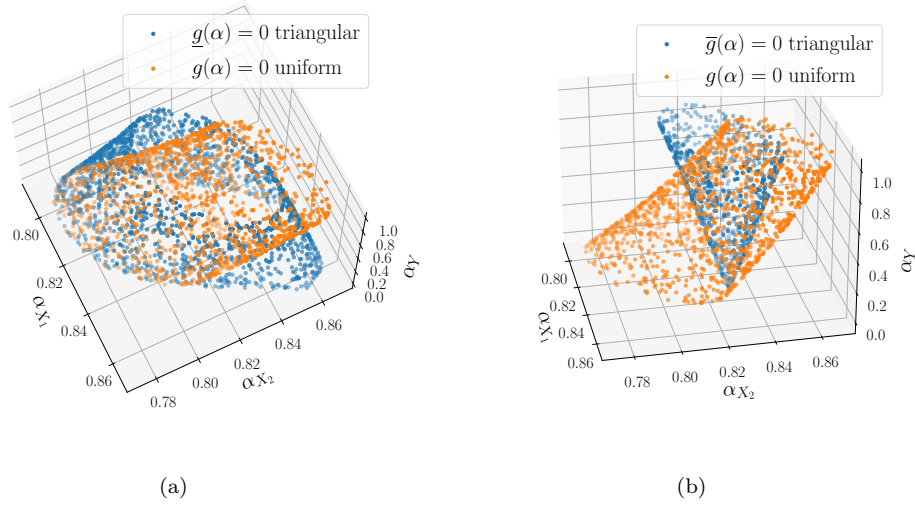


Figure 6: Comparison of $\underline{g}(\alpha) = 0$ in (a) and $\bar{g}(\alpha) = 0$ in (b) for the triangular and uniform uncertainty models.

420 obtained from the trapezoidal model. This is probably caused by the strong non-linearity of the limit-state function.

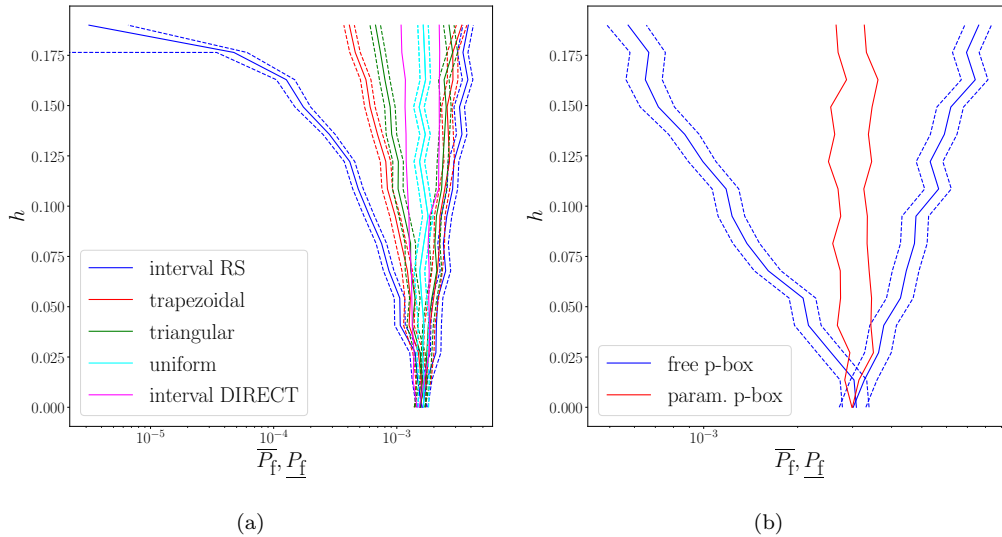


Figure 7: Robustness and opportuneness curves for the groups \mathbf{M}_1 (a) and \mathbf{M}_3 (b) for the Rosenbrock function.

421 **M₃ results.** Here, the free p-box and parametric p-box models are compared.
422 It is recalled that, for an equivalent support, the parametric p-box model
423 is more informative than the free p-box model which implies the bounds
424 on the probability of failure of the second model to be contained in the
425 bounds of the first model. The p-box models (free and parametric) are con-
426 structed by considering a Gaussian distribution on Y : $Y \sim \mathcal{N}(0.9, \sigma^2)$ with
427 $\sigma \in [1 - h, 1 + h]$. The parametric p-box results are obtained by perform-
428 ing an optimization using the DIRECT algorithm on σ . Fig. 7.(b) presents
429 the robustness and opportuneness curves. One can see a strong difference
430 in behavior as the bounds induced by the parametric p-box model barely
431 expand. This difference can again be explained by the strong non-linearity
432 of the model.

433 **M₄ and M₅ results.** The **M₄** comparison aims, firstly, at numerically illus-
434 trating the relation between the triangular possibility distribution and its
435 equivalent free p-box representation and, secondly, the link between the tri-
436 angular possibility distribution and its discretized DS model. The **M₅** com-
437 parison aims at numerically illustrating the link between the probabilistic
438 uniform cdf and its discretized DS model. Fig. 8 compares the limit-state
439 functions between the triangular model and its equivalent p-box at $h = 0.19$.
440 It does seem that the limit-state functions of both representations have the
441 same volume, though having a different shape. Note that, even if the differ-
442 ent scales make it hard to see, the failure domain $\bar{g}(\boldsymbol{\alpha}) \leq 0$ is still included
443 in the failure domain $\underline{g}(\boldsymbol{\alpha}) \leq 0$ for both representations as expected.

444 Fig. 9 compares the robustness and opportuneness curves for both com-
445 parisons and numerically confirms the expected results, despite the noise
446 induced by the probability of failure estimations.

447 4.3. Toy-case 2: a non-linear oscillator system

448 The second toy-case corresponds to an adapted version of a two-degree-
449 of-freedom oscillator as shown in Fig. 10 and seen in [30, 31]. The system is
450 composed of two masses m_p and m_s , two springs of stiffnesses k_p and k_s , two
451 damping ratios ζ_p and ζ_s and is subjected to a white noise base acceleration
452 of intensity S_0 . By denoting F_s as the force capacity of the secondary spring,
453 the reliability of the system is expressed through the following limit-state

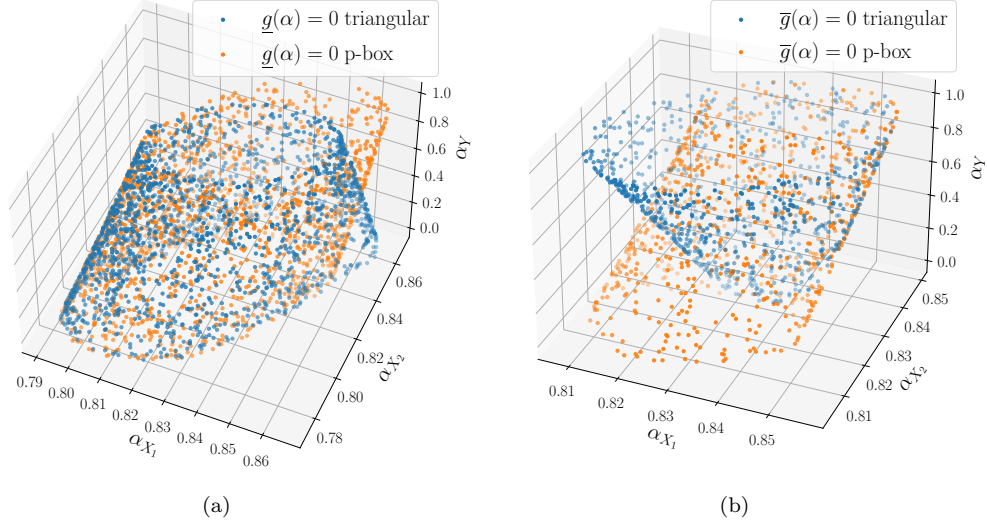


Figure 8: Comparison of $\underline{g}(\alpha) = 0$ in (a) and $\bar{g}(\alpha) = 0$ in (b) for the triangular and triangular-pbox uncertainty models.

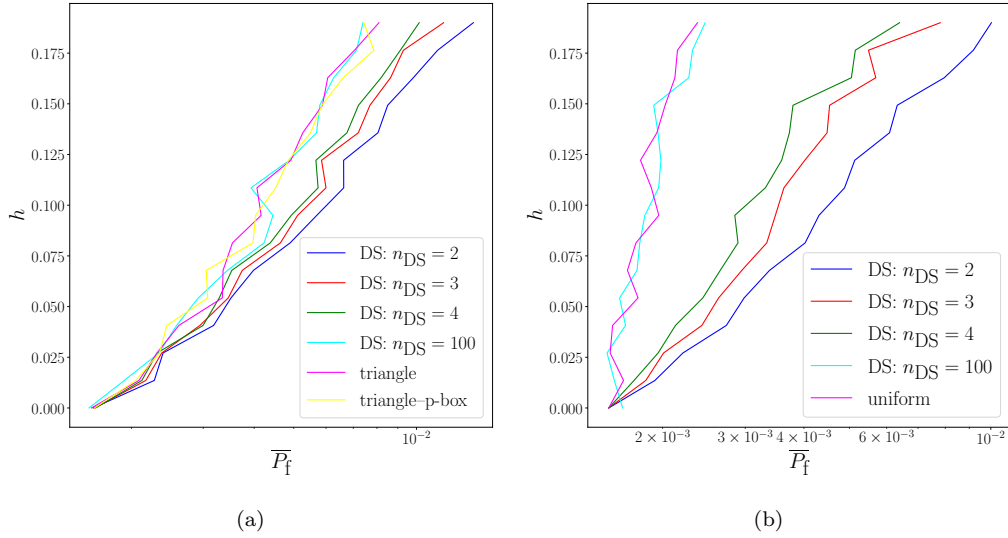


Figure 9: Robustness curves for the groups \mathbf{M}_4 (a) and \mathbf{M}_5 (b) for the Rosenbrock function.

454 function:

$$g(\mathbf{X}, \mathbf{Y}) = F_s - 3k_s \sqrt{\frac{\pi S_0}{4\zeta_s \omega_s^3} \left[\frac{\zeta_a \zeta_s}{\zeta_p \zeta_s (4\zeta_a^2 + r^2) + \gamma \zeta_a^2} \frac{(\zeta_p \omega_p^3 + \zeta_s \omega_s^3) \omega_p}{4\zeta_a \omega_a^4} \right]} \quad (19)$$

455 where $\gamma = m_s/m_p$ is the mass ratio, $\omega_p = (k_p/m_p)^{1/2}$ and $\omega_s = (k_s/m_s)^{1/2}$
456 the natural frequencies, $\omega_a = (\omega_p + \omega_s)/2$ the average frequency ratio, $\zeta_a =$
457 $(\zeta_p + \zeta_s)/2$ the average damping ratio and $r = (\omega_p - \omega_s)/\omega_a$ a tuning param-
458 eter. The random vector \mathbf{X} gathers $n_X = 3$ independent random variables
459 whose probabilistic modeling is given in Table 2. The epistemic vector \mathbf{Y}
460 is of dimension $n_Y = 5$ and its epistemic characteristics are given in Table
461 3. One supposes here that nominal values are known for the stiffnesses, the
462 damping ratios and the force capacity.

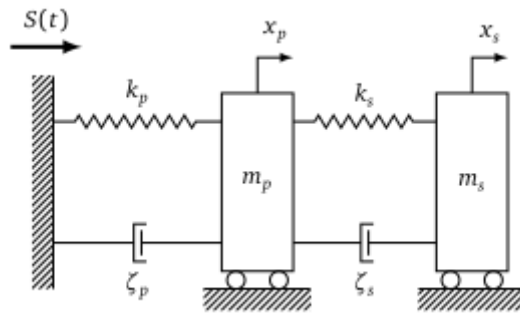


Figure 10: Two-degree-of-freedom damped oscillator.

463 The horizon of uncertainty is discretized into 10 values in $[0, 0.05]$. The
groups of comparison that are studied are \mathbf{M}_1 and \mathbf{M}_2 .

Table 2: Input probabilistic modeling of \mathbf{X} .

| Variable X_i | Distribution | Mean μ_{X_i} | δ |
|----------------------------------|--------------|------------------|----------|
| $X_1 = m_p$ (kg) | Lognormal | 1.5 | 10% |
| $X_2 = m_s$ (kg) | Lognormal | 0.01 | 10% |
| $X_3 = S_0$ (m.s ⁻²) | Lognormal | 100 | 10% |

464

465 \mathbf{M}_1 results. Before showing the robustness and opportuneness curves for all
466 representations, Fig. 11 compares these curves for the trapezoidal repre-
467 sentation estimated using the FORM-IS and Subset Simulation algorithms.
468 The curves obtained by evaluating the hybrid limit-state functions using the
469 vertex method [32] (which states that the extreme values of the limit-state
470 function are obtained at combinations of the extreme values of Y_i) instead of

Table 3: Epistemic characteristics of \mathbf{Y} .

| Variable Y_i | \tilde{Y}_i |
|----------------------------------|---------------|
| $Y_1 = k_p$ (N.m ⁻¹) | 1 |
| $Y_2 = k_s$ (N.m ⁻¹) | 0.01 |
| $Y_3 = \zeta_p$ (1) | 0.05 |
| $Y_4 = \zeta_s$ (1) | 0.02 |
| $Y_5 = F_s$ (N) | 11 |

471 an optimization algorithm are also given in the same figure. The curves sug-
 472 gest a high confidence in the results obtained with the FORM-IS algorithm
 and seem to confirm the hypothesis introduced with the vertex method.

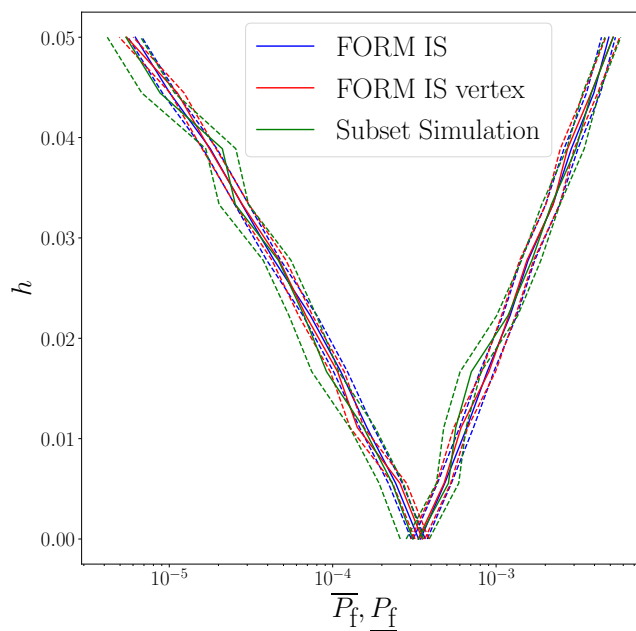


Figure 11: P_f estimators comparison for the oscillator case.

473 The robustness and opportuneness curves are given in Fig. 12.(a) and
 474 the corresponding VoI surface plot in Fig. 12.(b). Once again, the minimum
 475 probability of failure with the interval-RS model quickly decreases compared
 476 to the other representations including the interval-DIRECT model. This
 477 is not so much the case for the maximum probability of failure for which
 478

479 the highest values of $R_{\overline{P}_f}$ are obtained from the triangle representation to
 480 the uniform representation. Fig. 13.(a) gives the sensitivity measures from

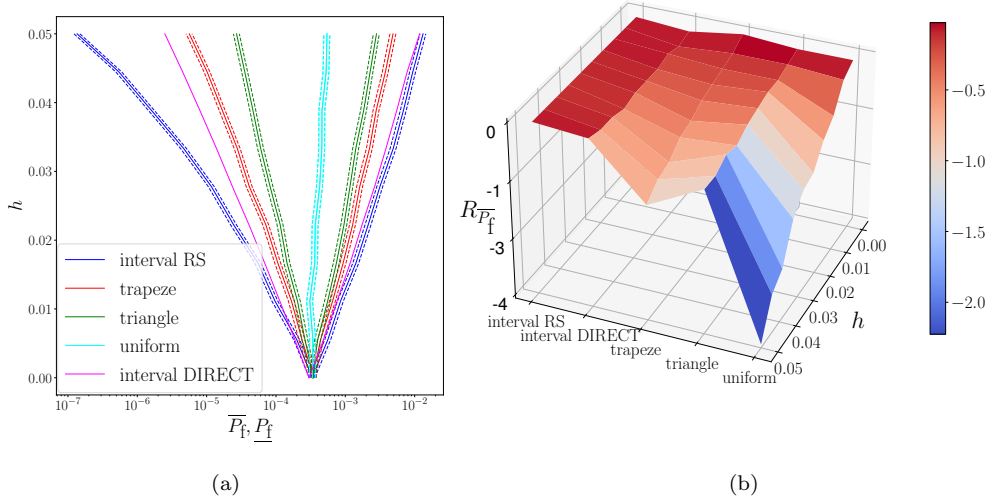


Figure 12: Robustness and opportuneness curves (a) and VoI metric (b) considering the \mathbf{M}_1 group for the non-linear oscillator case.

480
 481 the interval to the trapezoidal models and Fig. 13.(b) gives the sensitivity
 482 measures from the trapezoidal to the triangular models. It appears that the
 483 added information in F_s has, for both cases, the strongest influence on the
 484 robustness of the probability of failure even if it seems that k_p also has a
 485 strong influence.

486 **\mathbf{M}_2 results.** Here, the multi-parallelepiped uncertainty model is used to model
 487 the epistemic vector by considering an equal coefficient of linear correlation
 488 $\rho_{k_p \zeta_p} = \rho_{k_s \zeta_s} = \rho$. Fig. 14 presents the robustness and opportuneness curves
 489 for different values of the coefficient of correlation. The 95% confidence in-
 490 tervals are not depicted for the sake of clarity. As expected, the higher the
 491 coefficient of correlation in terms of absolute value, the narrower the bounds
 492 on the probability of failure. Nevertheless, the bounds will shrink signifi-
 493 cantly as soon as a non-zero coefficient of correlation is given but the results
 494 between a low or high coefficient do not considerably differ.

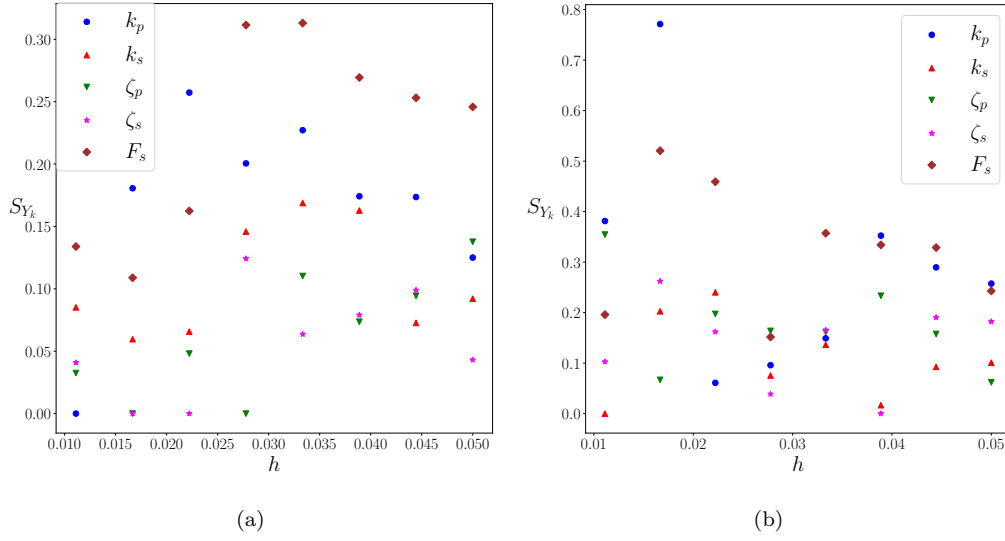


Figure 13: Sensitivity analysis interval-trapezoidal (a) and sensitivity analysis trapezoidal-triangular (b) for the oscillator case.

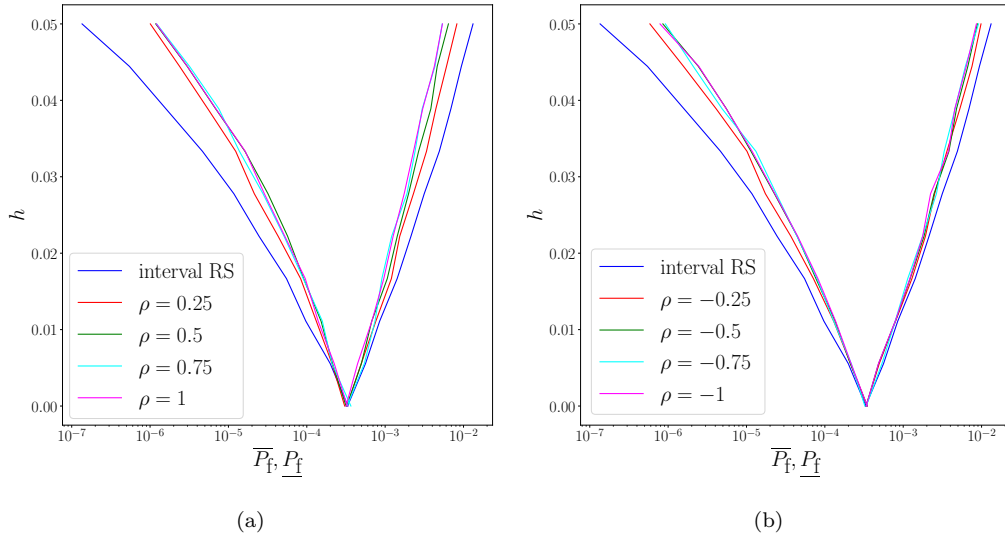


Figure 14: M_2 comparison for positive coefficients of correlation (a) and M_2 comparison for negative coefficients of correlation (b)

495 4.4. Industrial use-case: reliability assessment of penstocks

496 In this section, the methodology is applied to an industrial use-case rel-
 497 evant to the French electricity company EDF which concerns the reliability

498 study of penstocks [33, 34]. Note that this industrial application is illustra-
 499 tive: the choice of epistemic variables should be further substantiated. It is
 500 meant to demonstrate the feasibility of the methodology on a more complex
 501 industrial use-case. EDF operates more than 500 penstocks having a total
 502 length of over 300 km. Penstocks are pipes made of steel used to transport
 503 water under pressure from the water dam to the hydroelectric turbine. Due
 504 to thickness loss resulting from corrosion, their mechanical integrity must
 505 be justified. The usual justification relies on diagnoses involving thickness
 506 measurements and the evaluation of a deterministic margin factor MF.

507 To optimize MF, a general reliability approach was developed to assess
 508 annual probabilities of failure at year N of a given penstock. Two failure
 509 modes have been investigated: plastic collapse (parent metal) and brittle
 510 failure (welds), due to the presence of cracks appearing during the welding
 511 process. In the present application, only the second failure mode is considered
 512 since its reliability analysis is more complex:

- 513 • the limit-state function is locally non-differentiable and can be discon-
 514 tinuous;
- 515 • the annual probability of failure estimated here is a conditional prob-
 516 ability considering that the penstock passed a hydraulic test after its
 517 production in the workshop.

518 The conditional probability at year N can be expressed as:

$$P_f = \Pr(G_N \cap G_{N-1} < 0 \mid G_{ht} \geq 0) = \frac{\Pr(G_N \cap G_{N-1} \leq 0 \cap G_{ht} \geq 0)}{\Pr(G_{ht} \geq 0)} \quad (20)$$

519 where G_N is the limit-state function at year N , G_{N-1} the limit-state func-
 520 tion at year $N - 1$ and $G_{ht} \geq 0$ is the event that the penstock successfully
 521 passed the hydraulic test. As the G-function decreases over time due to the
 522 monotonic corrosion degradation, an equivalent expression is as follows:

$$P_f = \Pr(G_N \times G_{N-1} < 0 \mid G_{ht} \geq 0) = \frac{\Pr(G_N \times G_{N-1} \leq 0 \cap G_{ht} \geq 0)}{\Pr(G_{ht} \geq 0)} \quad (21)$$

523 In this work, the last expression will be preferred as it is better to reduce
 524 the number of intersecting events (from 3 to 2). The expressions of G_N ,
 525 G_{N-1} and G_{ht} are analytical but depend on too many parameters to be
 526 detailed here except for the parameters considered in the probabilistic and

527 epistemic vectors. The failure criterion corresponds to the failure assessment
 528 diagram given in [35]. The probabilistic vector \mathbf{X} is of dimension $n_X = 5$
 529 and its characteristics are given in Table 4 where R_m is the ultimate tensile
 530 strength, Δe_{extra} the extra thickness added to the design thickness, Δe_{corr}
 531 the thinning due to water and atmospheric corrosion, ε a parameter used to
 532 linearly express the yield strength in function of R_m and K_{IC} the tenacity of
 the material.

Table 4: Input probabilistic modeling of \mathbf{X} for the penstock use-case.

| Variable X_i | Distribution | Param 1 | Param 2 | Param 3 |
|------------------------------------------|--------------|---------|---------|---------|
| $X_1 = R_m$ (MPa) | Lognormal | 480 | 24 | - |
| $X_2 = \Delta e_{\text{extra}}$ (mm) | Normal | 0 | 0.25 | - |
| $X_3 = \Delta e_{\text{corr}}$ (mm) | Normal | 1 | 0.4 | - |
| $X_4 = \varepsilon$ (MPa) | Normal | 0 | 16.816 | - |
| $X_5 = K_{IC}$ (MPa. $\sqrt{\text{m}}$) | Weibull Min | 90 | 4 | 20 |

533
 534 The epistemic vector \mathbf{Y} is of dimension $n_Y = 3$ and its characteristics are
 535 given in Table 5 where e_{nom} is the nominal thickness of the pipe, Δe_{an} the
 536 annual loss of thickness and a the height of the crack. It should be noted
 537 that the values of the parameters of the probabilistic and epistemic variables
 538 were chosen in a large panel of values that represent the variety of all the
 539 penstocks operated by EDF in order to have an industrially relevant type of
 penstock which has a nominal probability of failure between 10^{-9} and 10^{-8} .

Table 5: Epistemic characteristics of \mathbf{Y} for the penstock use-case

| Variable Y_i | \tilde{Y}_i |
|-----------------------------------|---------------|
| $Y_1 = e_{\text{nom}}$ (mm) | 8 |
| $Y_2 = \Delta e_{\text{an}}$ (mm) | 0.06 |
| $Y_3 = a$ (mm) | 2 |

540
 541 The standard reliability analysis containing uniquely probabilistic vari-
 542 ables is performed using FORM-IS with OpenTURNS. Other techniques
 543 could also have been used such as Subset Simulation. It should be pointed out
 544 that calculating a conditional probability using RS theory is not as straight-
 545 forward as in Eqs. (15.a) and (15.b). Indeed, one cannot express in a trivial
 546 way the maximum or the minimum of the probability of failure as a function

547 of the maximum or minimum of both limit-states $G_N \times G_{N-1}$ and G_{ht} . Nev-
 548 ertheless in this case, as \mathbf{Y} has a greater impact on $G_N \times G_{N-1}$ than G_{ht} ,
 549 the following simplification is performed:

$$\bar{P}_f \approx \frac{\Pr [\min_{\Gamma(\boldsymbol{\alpha})} (G_N \times G_{N-1}) \leq 0 \cap G_{ht}(\boldsymbol{\alpha}^*) \geq 0]}{\Pr [G_{ht}(\boldsymbol{\alpha}^*) \geq 0]} \quad (22)$$

550 where $\boldsymbol{\alpha}^* = \arg \min (G_N \times G_{N-1})$. In this industrial use-case, only the max-
 551 imum probability of failure \bar{P}_f will be of interest. The results of the groups
 552 of comparison \mathbf{M}_1 , \mathbf{M}_2 and \mathbf{M}_3 are given in the following.

553 **\mathbf{M}_1 results.** The FORM-IS algorithm is, once again, the first choice to esti-
 554 mate the probabilities. Nevertheless, it is necessary to verify the results with
 555 another algorithm. Fig. 15 compares the robustness curves obtained with
 556 the FORM-IS and the Subset Simulation algorithms considering the interval
 557 model on \mathbf{Y} . Despite being less smooth, the results obtained with the Subset
 Simulation algorithm are very similar to those obtained with FORM-IS.

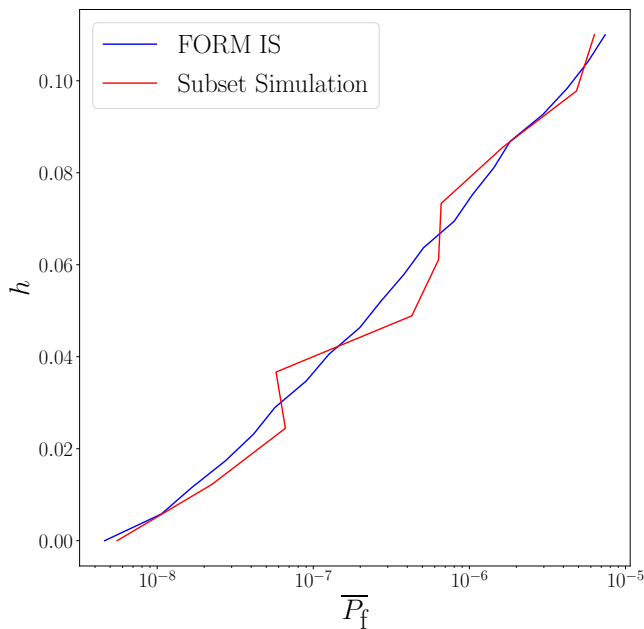


Figure 15: P_f estimators comparison for the penstock use-case.

558
 559 Fig. 16.(a) shows the robustness curves of \mathbf{M}_1 and Fig. 16.(b) shows
 560 the corresponding VoI surface plot of the VoI metric $R_{\bar{P}_f}$. Once again, the

561 probabilistic information of a uniform distribution considerably reduces the
 562 maximum probability of failure and therefore improves the robustness. The
 difference between both interval results is also quite significant.

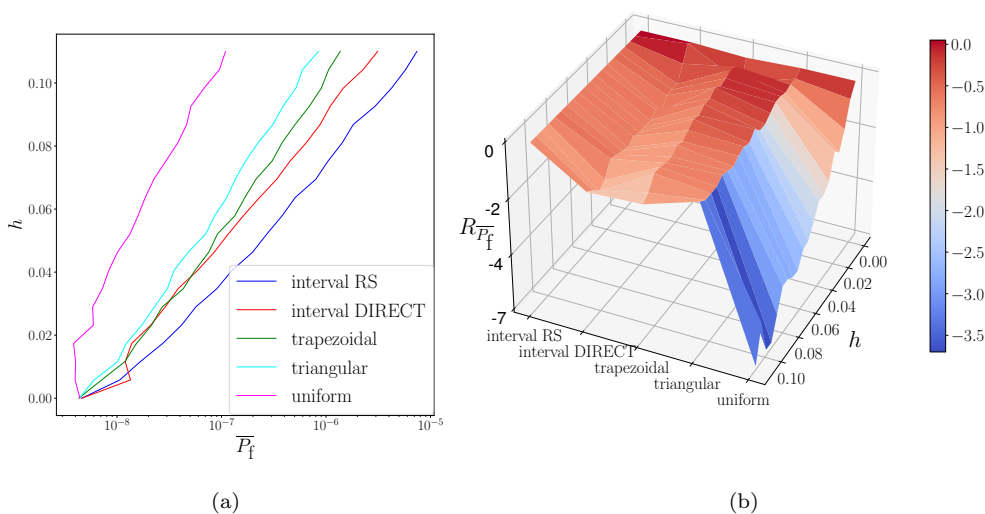


Figure 16: Robustness curves (a) and VoI metric (b) considering the \mathbf{M}_1 group for the penstock use-case.

563
 564 Fig. 17 presents the sensitivity results from the interval to the trapezoidal
 565 representations. The classification of the most influential variables on the
 566 information is quite clear whatever the horizon of uncertainty as the added
 567 information on e_{nom} has a strong influence, on K_{IC} a non-negligible influence
 568 and on Δe_{an} a very weak influence.

569 \mathbf{M}_2 results. Fig. 18.(a) presents the results with the multi-parallelepiped
 570 model by considering a coefficient of correlation $\rho = \rho_{Y_1 Y_2}$ between e_{nom} and
 571 Δe_{an} . It seems that a negative coefficient of correlation has no impact on the
 572 robustness while a positive coefficient has a very limited impact.

573 \mathbf{M}_3 results. The p-box model is constructed by considering a Gaussian dis-
 574 tribution for Y_i : $Y_i \sim \mathcal{N}(\tilde{Y}_i, \sigma_i^2)$ with $\sigma_i \in [\tilde{\sigma}_i(1-h), \tilde{\sigma}_i(1+h)]$ and
 575 $\tilde{\sigma} = [0.4, 0.003, 0.1]^\top$. For this case, the horizon of uncertainty belongs to
 576 $h \in [0, 0.5]$. The parametric p-box results are still obtained by performing

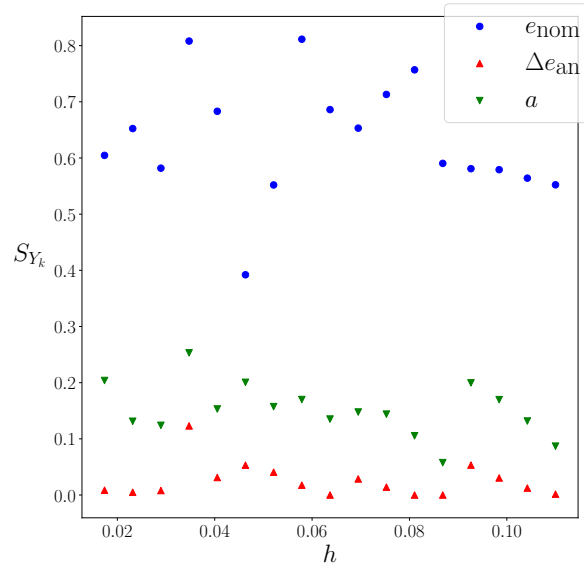


Figure 17: Sensitivity analysis interval-trapezoidal for the penstock use-case.

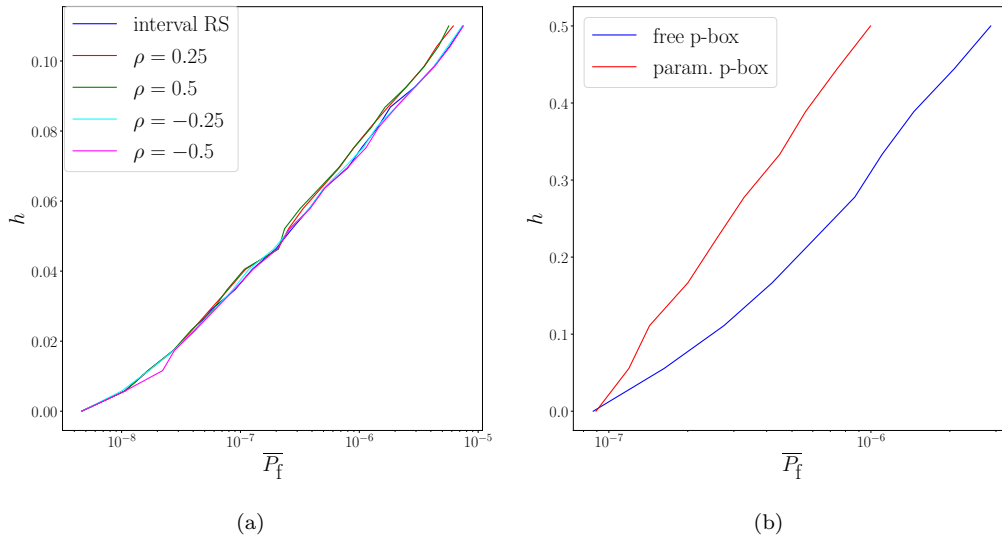


Figure 18: Robustness curves for the groups \mathbf{M}_2 (a) and \mathbf{M}_3 (b) for the penstock use-case.

577 an optimization using the DIRECT algorithm on σ . Fig. 18.(b) presents the
 578 robustness curves for both representations. The added information in the
 579 parametric p-box improves the robustness as expected.

580 5. Discussions

581 This section aims in a first place at summarizing all the results from
582 above with respect to the objective of this work which is to analyse the effect
583 of different models of uncertainty on a robustness analysis in the context of
584 HRA. The use-cases enable to numerically translate the links presented in
585 Fig. 1 by constructing and comparing opportuneness and robustness curves.
586 These links, and therefore the comparison, are divided into two main groups.
587 The first one, which involves the comparison groups M_1 , M_2 and M_3 , shows
588 in what extent a more informative uncertainty model may affect robustness
589 and opportunity. Indeed, adding information will often lead to a gain in
590 robustness (the model can tolerate more uncertainty) and a loss in oppor-
591 tunity (more uncertainty is needed for a positive unexpected outcome). In
592 the context of HRA, this notion is seen as a narrowing of the bounds of the
593 probability of failure until reaching a unique value for purely probabilistic or
594 deterministic models. The more the support of the epistemic variables grows
595 the more narrowing is observed. On the other hand, the more informative
596 a model is the more dependent the quantity of interest is on the hypothesis
597 made. Nevertheless, the benefits of acquiring information strongly depend
598 on the decision-making context. Indeed, in the case of safety assessment for
599 which very small probabilities of failure are estimated, a gain of informa-
600 tion is way more valuable if it affects the robustness curve rather than the
601 opportuneness curve.

602 The behavior of the numerical model (i.e., the limit-state functions in
603 the case of HRA) with respect to the epistemic variables also has a key role
604 on the value of information. For example, a monotonous behavior will yield
605 the same bounds on the probability of failure whether free or parametric
606 p-boxes are considered. A reduced convex set (i.e., more informative) will
607 have no impact on the robustness curve if the worst performance was initially
608 obtained at a point that is still contained in the more informative set. In
609 most practical cases, such information may unfortunately only be available
610 after the robustness analysis.

611 The second main group concerns the comparison groups M_4 and M_5 which
612 emphasize some links between different uncertainty models in the framework
613 of this paper. More precisely, it numerically confirms that possibility distri-
614 butions and DS structures may also be seen as free p-boxes and that proba-
615 bility and possibility distributions may be considered as DS structures (with
616 a loss of information that depends on the discretization process). This is

617 interesting for two main reasons. The first one is related to the fact that
618 all these uncertainty models with different interpretations and mathematical
619 foundations may be intimidating for an average decision maker. These links
620 show how different models can be closely related in the context of HRA. The
621 second reason is that it enables to widen the use of smart numerical methods
622 initially established for a specific uncertainty framework such as p-boxes for
623 which a lot of content is proposed.

624 Additionally, this section wants to clarify the use of the proposed method-
625 ology. The info-gap framework is initially built for taking robust decisions in
626 the context of strong uncertainty. The present work does certainly not aim
627 at ranking any uncertainty representation nor does it want to emphasize the
628 proposed methodology for performing an info-gap analysis. The choice of
629 an uncertainty model strongly depends on the available information and on
630 the context in which a decision must be made (e.g., a safety requirement).
631 The reader is referred to [16] for more insights into the use of the different
632 uncertainty representations. The info-gap method brings an additional tool
633 for confronting a decision to the hypotheses that were made in order to take
634 that decision. Therefore, it is complementary with the probabilistic frame-
635 work for decisions based on reliability quantities. The possible combination
636 of the different uncertainty models considered through random set theory
637 together with the info-gap framework offers a wide range of possibilities for
638 conducting a suitable robustness analysis on reliability quantities.

639 For example, in this work, the horizon of uncertainty is applied to the
640 supports of the epistemic variables for comparison purposes. In some appli-
641 cations, the support may be fixed but the uncertainty representation chal-
642 lenged. One may consider a nominal precise cumulative distribution function
643 that becomes a less informative DS structure (or wider p-box) at increasing
644 horizons of uncertainty until finally reaching the interval model. The way of
645 performing info-gap remains partially subjective as choices are made by the
646 decision-maker. Our idea is to face uncertainty the most objectively in order
647 to take a trustworthy decision.

648 **6. Conclusion**

649 In this paper, a methodology was proposed in order to analyse the robust-
650 ness of the upper bound of a probability of failure with respect to different
651 epistemic uncertainty representations in input. In the context of hybrid reli-
652 ability analysis, the random set framework is suitable to model and propagate

653 different representations of uncertainty to estimate reliability quantities of
654 interest such as bounds on a probability of failure. An info-gap robustness
655 analysis was performed by considering each type of uncertainty model in an
656 increasing support of the epistemic variables.

657 This methodology enabled to compare robustness and opportuneness
658 curves between uncertainty models that are more or less informative for
659 two academic examples and one industrial use-case related to the reliabil-
660 ity assessment of hydraulic penstocks. As expected, it is seen that increasing
661 the support of the epistemic variables leads to increasing the effect of the
662 choice of the uncertainty model on the bounds of the probability of failure
663 and therefore on the robustness analysis. The objective of this study is not
664 to determine the best representation of uncertainty, as this depends on the
665 available information, but to provide insights about the impact (in terms of
666 robustness) of the uncertainty model.

667 Such comparison is limited to relatively simple implementations of the
668 different components involved whether it is for the uncertainty models, the
669 use-cases or the application of info-gap. Moreover, the case of dependencies
670 within the random and epistemic variables and between both of them was
671 omitted. This is contradictory with the fact of confronting strong hypoth-
672 esis with the info-gap method. Finally, no comparison is given in terms of
673 function evaluations. Yet, hybrid reliability analysis combined to info-gap
674 requires a huge computational effort when no specific hypotheses are made
675 as it demands a very large number of evaluations of the initial limit-state
676 function. The question of feasibility with complex numerical codes should
677 also be part of the analysis.

678 Future work will compare the computational effort required as a function
679 of the uncertainty model used in a robustness analysis. This comparison
680 will depend on many factors and especially on hypotheses that are made
681 (for example, the monotony of the limit-state function with respect to the
682 epistemic variables), and the numerous strategies that have already been
683 developed to reduce the computational burden (for example, combination of
684 surrogate models with smart optimization algorithms).

685 **Appendix A. Standard reliability analysis**

686 The performance $z \in \mathbb{R}$ (assumed to be a scalar here for the sake of
687 simplicity) of a system is evaluated via an analytical or numerical model
688 $\mathcal{M}(\mathbf{x})$ where $\mathbf{x} \in \mathbb{R}^{n_x}$ with n_x the number of input variables. By considering

689 the convention that the performance must not exceed a given threshold $z_{\text{th}} \in$
 690 \mathbb{R} , the limit-state function $g(\cdot)$ is defined such that:

$$g(\mathbf{x}) = z_{\text{th}} - \mathcal{M}(\mathbf{x}). \quad (\text{A.1})$$

691 It follows the definition of the failure domain \mathcal{F} :

$$\mathcal{F} = \{\mathbf{x} \in D_{\mathbf{X}}, g(\mathbf{x}) \leq 0\} \quad (\text{A.2})$$

692 with $\mathcal{F}^0 = \{\mathbf{x} \in D_{\mathbf{X}}, g(\mathbf{x}) = 0\}$ the limit-state surface. In order to determine
 693 whether the system lies in the failure or safety domain, the uncertain input
 694 variables x_i ($i = 1, \dots, n_X$) are modeled using the probabilistic framework.
 695 The input vector is considered as a realization of the random vector $\mathbf{X} =$
 696 $(X_1, X_2, \dots, X_{n_X})^\top$ to which a supposedly known joint probability density
 697 function (pdf) $f_{\mathbf{X}}$ is attributed. One may then calculate a reliability quantity
 698 of interest such as the probability of failure P_f defined as:

$$P_f = \Pr[g(\mathbf{X}) \leq 0] = \int_{\mathcal{F}} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} = \int_{\mathbb{R}^{n_X}} \mathbb{1}_{\mathcal{F}}(\mathbf{x}) d\mathbf{x} \quad (\text{A.3})$$

699 where $\mathbb{1}_{\mathcal{F}}$ is the indicator function that is equal to one when the event $\mathbf{x} \in \mathcal{F}$
 700 is realized and zero when it is not. Several techniques exist to evaluate Eq.
 701 (A.3) such as sampling methods [24] or approximation methods [26].

702 **Appendix B. Uncertainty models**

703 *Interval model.* The interval representation only uses bounds to model the
 704 uncertainty on an input quantity Y_i . Therefore, the only hypothesis made
 705 here is that Y_i belongs to the interval $I_{Y_i} = [Y_i^L, Y_i^U]$ with Y_i^L the lower
 706 bound and Y_i^U the upper bound. Any value within the interval can be taken
 707 without any assumption about the fact that values are more likely than
 708 others. Note that it is totally different than assigning a uniform distribution
 709 over the interval since a uniform distribution is still a particular distribution
 710 and assumes an existing measure. When each Y_i is represented as an interval,
 711 the input space becomes the n_Y -box represented by the Cartesian product
 712 $I_Y = \times_{i=1}^{n_Y} I_{Y_i}$ where n_Y is the number of interval variables. After propagation
 713 through the numerical model $\mathcal{M}(\cdot)$, the performance is also an interval with
 714 no additional information. The bounds $[Z^L, Z^U]$ may be estimated using an
 715 optimization algorithm or the vertex method which states that the extreme
 716 values of the performance are obtained for combinations of the extreme values
 717 of Y_i . Methods to treat hybrid reliability problems involving both random
 718 and interval variables can be found in [36, 37].

719 *Convex model.* Convex models [11] are also a non-probabilistic representa-
720 tion of uncertainty which contains the interval model. It enables to add infor-
721 mation concerning possible dependencies between the input variables. The
722 ellipsoid and the parallelogram convex models are common examples. When
723 the input variables are independent, the convex model reduces to the n_Y -
724 box which characterizes the interval representation. In the same way as for
725 the interval model, the bounds on the performance function can be obtained
726 using an optimization algorithm in the convex set. The multi-parallelepiped
727 model [38] is used in this paper as it has the advantage of combining depen-
728 dent and independent variables. Moreover, a sample in this convex set can be
729 obtained from a sample $\mathbf{u} = (u_1, \dots, u_{n_Y})^\top$ of the hypercube $U = [-1, 1]^{n_Y}$
730 with the following transformation:

$$Y_i = \frac{Y_i^W}{\sum_{j=1}^{n_Y} |\rho(i, j)|} \sum_{k=1}^{n_Y} \rho_{ik} u_k + Y_i^C, \quad i = 1, 2, \dots, n_Y \quad (\text{B.1})$$

731 where $Y_i^C = \frac{Y_i^U + Y_i^L}{2}$ is the center point of the interval, $Y_i^W = Y_i^U - Y_i^L$ is
732 half the width of the interval and $\boldsymbol{\rho}$ is the correlation matrix. An example of
733 hybrid representation with random and multi-parallelepiped convex variables
734 can be found in [39] where bounds on the probability of failure are estimated
735 using Importance Sampling.

736 *Evidence theory.* Evidence theory (also called Dempster-Shafer (DS) theory)
737 [12, 40] assigns weights to subsets A , also called “focal sets”, of the power
738 set $\Omega(Y)$ using the following mass distribution ν :

$$\nu : \begin{cases} \Omega(Y) & \longrightarrow [0, 1] \\ A & \longrightarrow \nu(A) \end{cases} \text{ s.t. } \sum_{A \in \Omega(Y)} \nu(A) = 1. \quad (\text{B.2})$$

Two measures can then be defined, namely the belief function $Bel(\cdot)$ and
the plausibility function $Pl(\cdot)$, that bound the realization of any event E :

$$Bel(E) = \sum_{A \subseteq E} \nu(A) \quad (\text{B.3a})$$

$$Pl(E) = \sum_{A \cap E \neq \emptyset} \nu(A). \quad (\text{B.3b})$$

739 The belief measure can be seen as an upper probability of the event E while
740 the plausibility measure can be seen as a lower probability. When combin-
741 ing evidence theory to a reliability analysis [41], the belief and plausibility

742 measures enable to bound the probability of failure by considering the event
 743 $E = \{Y \in \mathcal{F}\}$. When the focal sets are singletons, the belief measure is equal
 744 to the plausibility measure and evidence theory reduces to probability theory.
 745 When there is only one focal set, it reduces to the interval representation.

746 *Possibility theory.* Possibility theory is a special case of evidence theory when
 747 focal sets are nested. Moreover, it is defined with the following possibility
 748 distribution π :

$$\pi : \Omega(Y) \rightarrow [0, 1] \text{ s.t. } \sup_{y \in \Omega(Y)} \pi(y) = 1. \quad (\text{B.4})$$

The triangular and trapezoidal distributions are common examples of possibility distributions. It follows the definition of two measures, namely the possibility $\Pi(\cdot)$ and the necessity $N(\cdot)$:

$$\Pi(E) = \sup_{y \in A} \pi(y) \quad (\text{B.5a})$$

$$N(E) = \inf_{y \notin A} (1 - \pi(y)) \quad (\text{B.5b})$$

749 where E is any event. α -cuts are commonly associated to a possibility distri-
 750 bution as they may be seen as nested confidence intervals with the following
 751 expression:

$$\left[\underline{y}_\alpha, \bar{y}_\alpha \right] = \{y, \pi(y) \geq \alpha\}. \quad (\text{B.6})$$

752 Baudrit and Dubois [18] propose a method to jointly propagate probabilistic
 753 and possibilistic information. In [42], possibility distributions are assigned to
 754 the parameters of probability distributions to create fuzzy random variables
 755 and estimate fuzzy failure probabilities.

756 *Probability boxes.* The probability box (p-box) framework assigns an imprecise
 757 cumulative distribution function (cdf) to the uncertain variable Y . The
 758 true, yet uncertain cdf, is bounded by an upper cdf \bar{F}_Y and a lower cdf \underline{F}_Y
 759 such that:

$$\bar{F}_Y(y) \leq F_Y(y) \leq \underline{F}_Y(y). \quad (\text{B.7})$$

760 Two groups of p-boxes are distinguished, namely free p-boxes and parametric
 761 p-boxes. Free p-boxes do not make any further assumptions other than the
 762 bounds on the true cdf. Any shape that respects the bounds and the prop-
 763 erties of a cdf is possible. Parametric p-boxes assume that the distribution

764 type is known or, at the very least, belongs to a parametric family. The un-
765 certainty lies in the parameters of the distribution (e.g., mean, variance) that
766 are modeled using simple intervals. Therefore, for equal bounds, parametric
767 p-boxes are more informative than free p-boxes by adding the information
768 concerning the distribution type. A comparison between free and paramet-
769 ric p-boxes in the context of surrogate modeling for reliability assessment
770 is proposed by Schöbi and Sudret [43]. Many uncertainty models already
771 mentioned can be represented as free p-boxes. Indeed, by considering the
772 event $\{Y \leq y\}$, plausibility and necessity measures can be seen as lower cdfs
773 while belief and possibility measures can be seen as upper cdfs. Probability
774 theory is retrieved when $\overline{F}_Y(y) = \underline{F}_Y(y)$. Monte Carlo sampling with p-box
775 variables can be performed by using inverse sampling as shown in [44]. A re-
776 view on more advanced techniques used to reduce the computational burden
777 when propagating p-box variables is available in [45].

778 References

- 779 [1] M. Lemaire, Structural Reliability, Wiley & Sons, 2009.
- 780 [2] E. Ardillon, et al., SRA into SRA: Structural reliability analyses into
781 system risk assessment, an ESReDA collective book, Det Norske Veritas
782 (2010).
- 783 [3] A. D. Kiureghian, Aleatory or epistemic? does it matter?, Structural
784 Safety 31 (2009) 105–112.
- 785 [4] S. Göhler, T. Eifler, T. Howard, Robustness Metrics: Consolidating
786 the multiple approaches to quantify Robustness, Journal of Mechanical
787 Design 138 (2016) 111407.
- 788 [5] Y. Ben-Haïm, Info-Gap Decision Theory: Decisions under Severe Un-
789 certainty, Elsevier, 2006.
- 790 [6] I. Takewaki, Y. Ben-Haïm, Info-gap robust design with load and model
791 uncertainties, Journal of Sound and Vibrations 288 (2005) 551–570.
- 792 [7] Y. Kanno, S. Fujita, Y. Ben-Haïm, Structural design for earthquake re-
793 siliance: Info-gap management uncertainty, Structural Safety 69 (2017)
794 23–33.

- 795 [8] J. Hall, R. Lempert, K. Keller, A. Hackbarth, C. Mijere, D. McInerney,
796 Robust climate policies under uncertainty: a comparison of robust deci-
797 sion making and info-gap methods, *Risk Analysis* 32 (2012) 1657–1672.
- 798 [9] E. Matrosov, A. Woods, J. Harou, Robust decision making and info-gap
799 decision theory for water resource system planning, *Journal of Hydrol-
800 ogy* 494 (2013) 43–58.
- 801 [10] A. Ajenjo, E. Ardillon, V. Chabridon, S. Cogan, E. Sadoulet-Reboul, Ro-
802 bustness evaluation of reliability assessments of penstocks using info-gap
803 method, in: e-proceedings of the 30th European Safety and Reliability
804 Conference and 15th Probabilistic Safety Assessment and Management
805 Conference, Venice, Italy, 2020.
- 806 [11] Y. Ben-Haïm, I. Elishakoff, *Convex models of uncertainty in applied
807 mechanics*, Elsevier, 1990.
- 808 [12] A. Dempster, Upper and lower probabilities induced by a multivalued
809 mapping, *The Annals of Mathematical Statistics* 38 (1967) 325–339.
- 810 [13] D. Dubois, Possibility theory and statistical reasoning, *Computational
811 Statistics & Data Analysis* 51 (2006) 47–69.
- 812 [14] S. Ferson, L. Ginzburg, Different methods are needed to propagate
813 ignorance and variability, *Reliability Engineering & System Safety* 54
814 (1996) 133–144.
- 815 [15] M. Beer, S. Ferson, V. Kreinovich, Imprecise probabilities in engineering
816 analyses, *Mechanical Systems and Signal Processing* 37 (2013) 4–29.
- 817 [16] E. Zio, N. Pedroni, Literature review of methods for representing uncer-
818 tainty, *Cahiers de la Sécurité Industrielle*, Technical Report, Foundation
819 for an Industrial Safety Culture (2013).
- 820 [17] F. Tonon, Using random set theory to propagate epistemic uncertainty
821 through a mechanical system, *Reliability Engineering & System Safety*
822 85 (2004) 169—181.
- 823 [18] C. Baudrit, D. Dubois, Joint propagation and exploitation of probabilis-
824 tic and possibilistic information in risk assessment, *IEEE Transactions
825 on Fuzzy Systems* 14 (2006) 593–608.

- 826 [19] D. Alvarez, F. Uribe, J. Hurtado, Estimation of the lower and upper
827 bounds on the probability of failure using subset simulation and random
828 set theory, *Mechanical Systems and Signal Processing* 100 (2018) 782–
829 801.
- 830 [20] D. Alvarez, On the calculation of the bounds of probability of events
831 using infinite random sets, *International Journal of Approximate Reasoning* 43 (2006) 241–267.
832
- 833 [21] D. Alvarez, J. Hurtado, J. Ramírez, Tighter bounds on the probability
834 of failure than those provided by random set theory, *Computers &
835 Structures* 189 (2017) 101–113.
- 836 [22] D. Finkel, Direct optimization algorithm user guide, Technical Report,
837 Center for Research in Scientific Computation, North Carolina State
838 University (2003).
- 839 [23] Y. Ben-Haim, Info-gap value of information in model updating, *Me-
840chanical Systems and Signal Processing* 15 (2001) 457–474.
- 841 [24] R. Melchers, Importance sampling in structural systems, *Structural
842 Safety* 6 (1989) 3–10.
- 843 [25] S. Au, J. Beck, Estimation of small failure probabilities in high di-
844 mensions by subset simulation., *Probabilistic Engineering Mechanics* 16
845 (2001) 263–277.
- 846 [26] J. Morio, M. Balesdent, Estimation of rare event probabilities in complex
847 aerospace and other systems: a practical approach, Elsevier, 2015.
- 848 [27] A. Saltelli, S. Tarantola, F. Campolongo, M. Ratto., *Sensitivity Analysis
849 in Practice: A Guide to Assessing Scientific Models*, Wiley, 2004.
- 850 [28] S. Ferson, W. Tucker, Sensitivity analysis using probability bounding,
851 *Reliability Engineering & System Safety* 91 (2006) 1435–1442.
- 852 [29] M. Baudin, A. Dutfoy, B. Iooss, A.-L. Popelin, OpenTURNS: An
853 industrial software for uncertainty quantification in simulation, in:
854 R. Ghanem, D. Higdon, H. Owhadi (Eds.), *Handbook of Uncertainty
855 Quantification*, Springer, 2017, pp. 2001–2038.

- 856 [30] A. D. Kiureghian, M. D. Stefano, Efficient algorithm for second-order
857 reliability analysis, *Journal of engineering mechanics* 117 (1991) 2904–
858 2923.
- 859 [31] V. Chabridon, M. Balesdent, J.-M. Bourinet, J. Morio, N. Gayton, Eval-
860 uation of failure probability under parameter epistemic uncertainty: ap-
861 plication to aerospace system reliability assessment, *Aerospace Science
862 and Technology* 69 (2017) 526–537.
- 863 [32] W. Dong, H. Shah, Vertex method for computing functions of fuzzy
864 variables, *Fuzzy Sets and Systems* 24 (1987) 65—78.
- 865 [33] E. Ardillon, P. Bryla, A. Dumas, A semi-probabilistic approach for op-
866 timizing quantiles in the diagnoses of hydropower penstock pipes, *Pro-
867 ceedings of the 54th ESReDA seminar* (2018).
- 868 [34] P. Bryla, E. Ardillon, A. Dumas, Probabilistic models for penstock
869 integrity assessment, *Proceedings of the ESReL 2020 conference* (2020).
- 870 [35] B. 7910, Guide to methods for assessing the acceptability of flaws in
871 metallic structures., *British Standard Institute* (2015).
- 872 [36] X. Du, A. Sudjianto, B. Huang, Reliability-based design under the
873 mixture of random and interval variables, *Journal of Mechanical Design*
874 127 (2005) 1068–1076.
- 875 [37] C. Jiang, G. Lu, L. Liu, A new reliability analysis method for uncertain
876 structures with random and interval variables, *International Journal of
877 Mechanics and Materials in Design* 8 (2012) 169–182.
- 878 [38] B. Ni, C. Jiang, X. Han, An improved multidimensional parallelepiped
879 non-probabilistic model for structural uncertainty analysis, *Applied
880 Mathematical Modelling* 40 (2016) 4727–4745.
- 881 [39] X. Liu, I. Elishakoff, A combined Importance Sampling and active learn-
882 ing Kriging reliability method for small failure probability with random
883 and correlated interval variables., *Structural Safety* 82 (2020) 101875.
- 884 [40] G. Shafer, *A mathematical theory of evidence*, NJ: Princeton (1976).

- 885 [41] Z. Zhang, C. Jiang, X. Han, D. Hu, S. Yu, A response surface approach
886 for structural reliability analysis using evidence theory, *Advances in*
887 *Engineering Software* 69 (2014) 37–45.
- 888 [42] M. Valdebenito, M. Beer, H. Jensen, J. Chen, P. Wei, Fuzzy failure
889 probability estimation applying intervening variables, *Structural Safety*
890 83 (2020) 101909.
- 891 [43] R. Schöbi, B. Sudret, Structural reliability analysis for p-boxes using
892 multi-level meta-models, *Probabilistic Engineering Mechanics* 48 (2017)
893 27–38.
- 894 [44] H. Zhang, R. Mullen, R. Muhanna, Interval Monte Carlo methods for
895 structural reliability, *Structural Safety* 32 (2010) 183–190.
- 896 [45] M. Faes, M. Daub, S. Marelli, E. Patelli, M. Beer, Engineering analysis
897 with probability boxes: A review on computational methods., *Structural*
898 *Safety* 93 (2021) 102092.