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1 **Accounting for end-user preferences in earthquake early warning systems**

2 Thomas Le Guenan¹, Farid Smai, Annick Loschetter, Samuel Auclair, Daniel Monfort, Nicolas Taillefer
3 and John Douglas²

4 BRGM – Risks and Prevention Division (DRP)

5 3 avenue C. Guillemin

6 BP 36009

7 45060 ORLEANS Cedex 2

8 France

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11 **Abstract:**

12 Earthquake early warning systems (EEWSs) that rapidly trigger risk-reduction actions after a
13 potentially-damaging earthquake is detected are an attractive tool to reduce seismic losses. One
14 brake on their implementation in practice is the difficulty in setting the threshold required to trigger
15 pre-defined actions: set the level too high and the action is not triggered before potentially-
16 damaging shaking occurs and set the level too low and the action is triggered too readily. Balancing
17 these conflicting requirements of an EEWS requires a consideration of the preferences of its
18 potential end users. In this article a framework to define these preferences, as part of a participatory
19 decision making procedure, is presented. An aspect of this framework is illustrated for a hypothetical
20 toll bridge in a seismically-active region, where the bridge owners wish to balance the risk to people
21 crossing the bridge with the loss of toll revenue and additional travel costs in case of bridge closure.
22 Multi-Attribute Utility Theory (MAUT) is used to constrain the trigger threshold for four owners with
23 different preferences. We find that MAUT is an appealing and transparent way of aiding the
24 potentially controversial decision of what level of risk to accept in EEW.

25 **Keywords:** earthquake early warning (EEW), decision making, end-user preferences, bridges,
26 thresholds, Multi-Attribute Utility Theory (MAUT)

¹ Corresponding author. Email : t.leguenan@brgm.fr, Tel : +33 (0)2.38.64.38.53, Fax : +33 (0)2.38.64.35.49.

² Now at: University of Strathclyde, Department of Civil and Environmental Engineering, Level 5, 75 Montrose Street, Glasgow, G1 1XJ, United Kingdom.

27 1. Introduction

28 In the past decade there has been increasing interest in earthquake early warning systems (EEWSs)
29 as a tool to reduce seismic losses. An EEWS seeks to provide a warning of potentially-damaging
30 shaking at a location (or locations) of interest at least a few seconds before this shaking arrives. For
31 example, an EEWS is installed as part of the Shinkansen (the Japanese high-speed railway network) to
32 bring trains to a controlled stop if seismic ground motions over a certain threshold are predicted.
33 Such systems rely on the fact that damaging seismic waves (generally the S phase) travel at a speed
34 that is relatively slow with respect to electronic signals that carry the warning. Consequently for
35 locations beyond the 'blind zone' close to the epicentre there is sufficient time to detect and
36 characterise an earthquake and then estimate the ground motions at sites of interest (e.g. Allen,
37 2012). A number of EEWS have been installed for testing around the world based on various software
38 packages, e.g. ElarmS (Wurman et al., 2007), PRESTo (Satriano et al., 2011), UrEDAS (Nakamura and
39 Saita, 2007) and Virtual Seismologist (Cua and Heaton, 2007). The development of: more reliable and
40 faster procedures for detecting, locating and characterising earthquakes, and better methods to
41 estimate expected ground motions at a site, continue apace. The question of how sure one needs to
42 be before triggering a risk-reduction action, however, is less commonly considered. This is because
43 end-user needs are often neglected during the conception and installation of EEWSs (Auclair et al.,
44 2015). This is the focus of this article, which provides a framework to account for the preferences of
45 different people that could be affected by the decision of whether or not to trigger an action. After
46 developing the mathematical background of the proposed approach, the procedure is applied to a
47 hypothetical situation of a highway toll bridge in a seismically-active region.

48 In currently-installed EEWSs in Mexico and Japan quite a low threshold is used, thereby passing all
49 information on potential shaking at a site to the end user to decide how to react. This is appropriate
50 when a system covers large area with many different types of end users, each with their own needs.
51 For highly-seismic regions with a large set of observations it could be possible to calibrate the
52 threshold level by trial-and-error. For example, the UrEDAS system used to stop Shinkansen trains
53 was calibrated using observations of damage to railway embankments and bridges in previous
54 earthquakes. Such an empirical approach is, however, not possible for regions of lower seismic
55 hazard where information on how the system performs in practice is often lacking.

56 There are various studies concerning the fixing of the appropriate threshold for EEWS using different
57 mathematical approaches. For example, Zollo et al. (2010) propose to fix several thresholds within a
58 two-parameter space (comprised of the average period of the P-wave signal and the peak
59 displacement) but their approach is based on the hazard rather than by considering the potential

60 losses connected with a potential risk-reduction action. On the other hand, Wang et al. (2012)
61 develop an approach that does consider losses but the loss model is simple and user preferences are
62 not taken into account when setting the threshold. Iervolino et al. (2007) use a more sophisticated
63 loss model but again the preferences of the user are not considered. The recent proposal by Wu et
64 al. (2013) for an ePAD system allows consideration of whether a user is risk averse (i.e. is biased
65 towards taking fewer risks even if this means missing out on some rewards) but its application is only
66 shown assuming risk neutrality. User preference is incorporated through a cost model determined by
67 the user, which includes a model for the lead time as well. Constructing a cost model requires
68 translating often vague preferences into actual numbers, which is not easy. In addition, because it is
69 based on cost-benefit analysis (CBA) it requires costing everything, including the monetary value of a
70 life saved. In addition, all these previous studies consider that the EEWS has already been installed.

71 This article differs from previous works in this domain by: using an approach to define the triggering
72 threshold that allows preferences of the user to be taken into account (e.g. does the user accept a
73 very low level of risk even if this means additional cost?), employing a technique that does not
74 require assigning a monetary value to every aspect, and by considering whether the EEWS should be
75 installed based on the user's preferences.

76 **2. Participatory decision making in EEWS**

77 Because of the short interval between the EEWS detecting a possibly-damaging earthquake in the
78 vicinity and the arrival of the shaking only automatic actions (e.g. switching off of gas valves or
79 stopping a train) can realistically be triggered by EEWSs. Therefore, before defining the criteria for
80 making the automatic decision of whether to trigger, certain actions have to be decided on
81 beforehand. In view of this, decision making in the pre-earthquake period for the calibration of EEWS
82 is the focus of this article.

83 Four distinctive roles can be defined within the context of decision making: the decision maker (or
84 end user), who is the person or institution in charge of making the final decision on risk reduction
85 (e.g. directors of a specific building); the stakeholders, who are the people impacted by the decision
86 (e.g. workers in a specific building); the analysts, who provide guidance to the decision makers; and
87 experts, who may help with specific aspects of the procedure. While the final decision is made by the
88 decision maker only, it must gain acceptance from all stakeholders. Consequently we recommend
89 that all stakeholders are involved within a participatory decision-making process, at least as suppliers
90 of information and opinions.

91 The benefits and potential difficulties in using a participatory approach for decision making are
92 discussed by Douglas et al. (2012) using various examples, generally from fields other than
93 earthquake risk management. These benefits include: an improvement in the quality of the decision
94 made because inputs from many parties are used; enhanced legitimacy of the decision because the
95 views of all interested groups are considered; and, through the participatory process, the public
96 becomes more aware of the problem and hence the risk is partially mitigated simply by greater
97 awareness of the issues. The principal difficulties in this approach are its higher cost, additional
98 complexity and the longer time required over a unilateral procedure. As noted by Douglas et al.
99 (2012), however, in a democratic society some sort of participatory process is obligatory. Douglas et
100 al. (2012) give examples of the success of participatory decision making in contexts ranging from the
101 issuance of flood warnings to transport planning and the approval of new medicines.

102 *2.1. Proposed framework*

103 The overall framework for participatory decision making that we propose is based on and freely
104 adapted from Participatory Integrated Planning (PIP) summarized by Castelletti and Soncini-Sessa
105 (2006). This procedure was first developed for integrated water-basin management and is here
106 adapted for EEW. Even though the context and the objectives of water-basin management and EEW
107 are sometimes very different, we feel that the framework of the PIP is sufficiently broad so that it can
108 encompass all aspects of EEWS (and earthquake risk management, in general).

109 Figure 1 represents the various steps included in the decision-making procedure proposed for EEWSs.
110 The goal of this procedure is to make the decisional framework clearer. Each step should be seen as a
111 milestone where the analysts and the stakeholders need to communicate in both directions. This
112 procedure is iterative, meaning that it is sometimes necessary to go back a few steps and reach a
113 new agreement. To implement the full procedure is time-consuming and potentially costly but
114 sometimes necessary if the decisions are to be shared. The apparent complexity of the procedure
115 can always be adapted to the situation (and to the money and time available): in the case of a single
116 decision maker and a single criterion, it can be rapidly completed. Again the goal here is to make
117 visible all the decisions that are taken but very often in an implicit manner.

118 Because of length constraints not all aspects of the proposed procedure are illustrated here to the
119 same depth. In particular, we present certain parts of Multi-Attribute Utility Theory (MAUT), which is
120 used as a basis of the main steps, in detail but we do not consider the compromise and reassessment
121 of the alternatives. These aspects are covered in more depth in the project deliverable on which this
122 article is based (Le Guenan et al., 2014).

123 **3. Multi-attribute utility theory**

124 To structure the main steps of the proposed framework, we have chosen to use MAUT, although
125 more familiar approaches such as CBA could be envisioned. As discussed below, MAUT has various
126 advantages over CBA, although care has to be taken when it is implemented as its inputs require
127 judgement and calibration. The foundations of MAUT were first developed by von Neumann and
128 Morgenstern (1953). Here we use the terminology of Keeney and Raiffa (1993), to which the
129 interested reader is referred for more details on the theory and further references. In MAUT all
130 criteria of relevance to a decision are assessed using a utility function, which is normalised between
131 zero (the least preferred value) and unity (the most preferred). These utility functions are
132 constructed through elicitation of the decision makers, thereby enabling their preferences to be
133 included. A global utility function is constructed by aggregating individual utility functions for each
134 attribute.

135 MAUT is used here because of the following reasons. Firstly, it provides a structure for the main steps
136 of the general approach presented in Figure 1, namely: criteria and indicators definition, assessment
137 of alternatives and evaluation. Secondly, it allows several criteria to be brought into the decision-
138 making process, thereby identifying trade-offs and comparing various objectives in a consistent
139 manner. Thirdly, it explicitly accounts for uncertainties, which are predominant within EEW. Finally, it
140 can take into account risk aversion (non-linear preferences). Specifically with respect to CBA, MAUT
141 has two principal advantages. Firstly, it can account for any kind of indicator and not just monetary
142 values. Secondly, the proposed criteria are based on the decision maker's preferences, whereas in a
143 rigorous CBA all costs and benefits should be included, even those that are not of concern to the
144 decision maker. This can lead to difficulties within the context of a participatory approach since the
145 entire society may have to be considered.

146 Previous uses of MAUT within a risk management context are few. Kailiponi (2010) presents a use of
147 MAUT for the 'Evacuation Responsiveness by Government Organizations' project to help emergency
148 managers faced with critical evacuation decisions (implying conflicting objectives as well as high
149 levels of uncertainty). His illustrative model identifies risk thresholds at which evacuation actions
150 should be taken by emergency managers in a storm surge scenario, with forecasts at 12 and 9-hour
151 intervals. He defines four levels of actions: no action, advice, mild evacuation and urgent evacuation,
152 and he uses three attributes: cost of life, economic cost and organizational cost. An additive utility
153 function is used.

154 **4. EEWS for a hypothetical bridge**

155 To test the feasibility of the proposed framework and MAUT, we consider a hypothetical case study
156 of a toll bridge in a seismically-active region (this corresponds to the ‘Context and objectives’ step
157 indicated in Figure 1). The action that is considered here is to use an EEWS based on an existing
158 regional network of sensors that would trigger a barrier at the entrance of the bridge, effectively
159 stopping vehicles entering the bridge when strong shaking is anticipated. A decision needs to be
160 made to set up the system in the “best” way possible, i.e. according to the decision maker’s
161 preferences. The system can be tuned with a Critical Probability P_C that the bridge is damaged to a
162 level equal to or greater than Damage State (DS) 3 (out of five, where DS5 is complete damage) on
163 the damage scale specified for bridges by FEMA (2003), i.e.:

$$\text{Action if: } P(DS \geq DS3) > P_C \quad (1)$$

164 For this case study, the goal is to find the value of P_C that will maximise the decision maker’s utility.
165 Amongst all the possible values for P_C , a probability of 1 means that the barrier is never lowered.
166 Hence, this value represents the so-called “alternative 0” or “business as usual”: the final decision
167 implied by this potential result is not to install or use the EEWS for the bridge (this is the
168 ‘Alternatives’ step in Figure 1).

169 To assess the ‘barrier-lowering’ action and to optimize its settings, the criteria or objectives of the
170 EEWS must be defined. The first criterion is to reduce the seismic risk or “Maximize the safety of
171 persons”. This risk arises when there are vehicles on the bridge and there is a chance of the bridge
172 being damaged by the earthquake. Consequently, a quantitative indicator corresponding to this
173 criterion is the number of “vehicles at risk” defined as the number of vehicles on the bridge while the
174 bridge is in a damage state higher or equal to DS3. This, however, cannot be the only objective or the
175 consequence would be to always close the bridge as then the defined indicator would be certain to
176 stay at null. Other objectives, linked to the service offered by the bridge must be added, i.e.:
177 “Maximize public satisfaction” and “Minimize the economic cost due to false alarms”. Both of these
178 criteria were represented by the same indicator: the number of false alerts in a five-year interval (see
179 following discussion for the rationale of this indicator). For our case study, a false alert means that
180 the action was triggered but DS3 was not reached. A fourth criterion is defined corresponding to the
181 desire to keep the cost of the EEWS to a minimum, i.e.: “Limit the risk management cost”. This
182 criterion is also needed as the efficiency of the system could be improved with infinite resources
183 (allowing installation of an infinite amount of sensors, for example). The related quantitative
184 indicator is, hence, the “Annual cost of Risk Management” and can be expressed as a percentage of
185 the total budget for operating the bridge. A summary of the criteria and indicators for this case study
186 are shown in Figure 2. Note that one indicator can represent several criteria or proxy-criteria. The

187 annual cost of risk management also indirectly corresponds to “maximize public satisfaction”
188 because if the cost is kept low then toll fees or taxes also remain low thereby satisfying the public. To
189 “limit the number of missed alarms” means that the system should work as planned and hence
190 should “minimize the number of endangered vehicles”. The VaR indicator also represents the proxy-
191 criteria “limit the number of missed alarms”.

192 It should be made clear that choosing appropriate criteria and associated indicators is critical to
193 obtaining useful results. They need to be informative, i.e. they capture aspects that are useful to the
194 decision maker, and exhaustive, i.e. all the criteria together should cover *all* the principal aspects that
195 the stakeholders and the decision maker are interested in. Choosing different criteria and indicators
196 could lead to different decisions being returned by MAUT as the most preferable. Here we have
197 chosen indicators that appear appropriate for our case study but if this procedure was to be
198 implemented for a real bridge then further effort should be spent on the choice of the criteria and
199 indicators. The choice of criteria in particular should be made in a participatory way and remain
200 transparent throughout the application of the method. The analyst can then help to choose an
201 optimal set of indicators that can represent all the desired criteria. Keeney and Raiffa (1993)
202 recommend that the set of indicators should be complete, operational, decomposable, non-
203 redundant and minimal. They also acknowledge that there can be several sets of indicators fitting the
204 same problem.

205 *4.1. Bayesian network for loss assessment*

206 The next step is to build a model able to compute each indicator as a function of P_c and of the
207 various hypotheses made. The model should be able to simulate for a pre-defined temporal horizon a
208 series of events and their corresponding consequences on the bridge, as well as the predictions
209 made by the EEWS. There is a difference between the simulated result (reproduction of “real”
210 events) and the predictions that form the basis for computing the losses (here, vehicles at risk) and
211 the number of false alarms. As most relationships are probabilistic, we use a Bayesian network,
212 which provides a powerful framework for performing inferences, by using the Markov Chain Monte
213 Carlo (MCMC) technique (see e.g. Neapolitan, 2004, for details on Bayesian networks): this
214 corresponds to the step ‘Models’ in Figure 1. The complete Bayesian network developed for the case
215 study is shown in Figure 3.

216 We use a fixed temporal horizon of 50 years to compute the indicators but we actually computed a
217 large number of possible horizons in order to account for rare events: the performance of the EEWS
218 and hence the utility of the decisions are highly dependent on the events that the system will face.

219 For example, if no major events occur once the system is installed then all the operating costs and
 220 the possible false alarms are not justified.

221 In Figure 3, the top node is “M, R”, where M corresponds to the earthquake moment magnitude and
 222 R the source-to-site distance (here distance to the surface projection of the rupture). These are
 223 actually two different variables, but they represent the same event. As this node is the parent node
 224 of the entire graph, it is only characterized by its prior probability: P(M, R). In this study, for each
 225 event, its location is drawn randomly from the seismogenic zone (Figure 4), which is assumed to be
 226 of rectangular shape with dimensions 500 km x 50 km and with depth 20 km. The bridge is placed in
 227 the middle of one of the longest sides. R is the distance between the bridge and the location of the
 228 event and so P(R) can be easily estimated with a large number of drawn random locations. For P(M),
 229 the basic approach of probabilistic seismic hazard assessment studies (PSHA) is followed, i.e. it is
 230 assumed that the seismicity inside a source zone is a time-independent process characterized by a
 231 Poisson distribution. Thus, seismicity is defined using the Gutenberg-Richter relation: $\log N = a - bM$,
 232 truncated at M_{MIN} and M_{MAX} . N is the average number of events where the magnitude is greater or
 233 equal to M. We assume the following parameters: $a = 3.3$; $b = 0.74$; $M_{\text{MIN}} = 3$; and $M_{\text{MAX}} = 8$, which
 234 roughly correspond to the situation near Istanbul (SHARE, Giardini *et al.*, 2013). For each event, the
 235 Intensity Measure “IM” node is computed using a ground motion prediction equation: $P(\text{IM} | M, R)$, for
 236 which we used the model of Akkar and Bommer (2010).

237 The Damage State “DS” can then be computed using a fragility curve for the bridge: $P(\text{DS} | \text{IM})$. This
 238 curve is presented in Figure 5 (Taillefer *et al.*, 2014).

239 This path, $P(\text{DS} | \text{IM}) \times P(\text{IM} | M, R) \times P(M, R)$, simulates the effect of future earthquakes on the bridge.
 240 The other part of the Bayesian network simulates how the EEWS reacts to the earthquakes.

241 The EEWS makes a prediction of M and R: “ \tilde{M}, \tilde{R} ”. For sake of simplicity, we assume that the error in
 242 location is negligible (Iervolino *et al.*, 2009) and that the probability of the predicted magnitude
 243 follows a normal distribution with parameters $\mu = M$ and $\sigma = 0.5$ (Allen and Kanamori, 2003), i.e.:

$$P(\tilde{M} | M) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\tilde{M}-M)^2}{2\sigma^2}} \quad (2)$$

$$\tilde{R} = R \quad (3)$$

244 The node “A” represents the action taken by the system. It is a discrete variable: for $A = 1$, the action
 245 is performed; else $A = 0$ and the action is not performed. The action is defined using equation (1), but
 246 in the system, no real-time measurement of DS is made: only \tilde{M} and \tilde{R} are estimated. Thus, we need
 247 to have a relationship in the form: $P(A | \tilde{M}, \tilde{R})$. In order to determine this conditional probability, we

248 first use a subset of the Bayesian network (see Figure 6), allowing us to compute $P(DS|\tilde{M}, \tilde{R})$. Using
 249 the properties of Bayesian networks (see e.g. Neapolitan, 2004 for more details), we can use the law
 250 of total probability and the Markov condition in order to obtain:

$$P(DS|\tilde{M}, \tilde{R}) = \int_{IM} P(DS|IM) \times P(IM|\tilde{M}, \tilde{R}) dIM \quad (4)$$

$$P(DS|\tilde{M}, \tilde{R}) = \iint_{IM, M, R} (DS|IM) \times P(IM|M, R) \times P(M, R|\tilde{M}, \tilde{R}) dIM dM, R \quad (5)$$

251 Applying the Bayes theorem:

$$P(M, R|\tilde{M}, \tilde{R}) = \frac{P(\tilde{M}, \tilde{R}|M, R) \times P(M, R)}{\int_{M, R} P(\tilde{M}, \tilde{R}|M, R) \times P(M, R)} \quad (6)$$

252

253 The integrals in the previous equations are then computed using the MCMC algorithm allowing
 254 computation of $P(DS|\tilde{M}, \tilde{R})$. This conditional probability is represented in Figure 7. So given \tilde{M}, \tilde{R}
 255 and P_c , A is easily determined by using the graph in Figure 7: if the point corresponding to the
 256 estimated parameters lies below the curve corresponding to the fixed P_c , then $A = 1$, otherwise, $A =$
 257 0.

258 The lead time “ ΔT ” is modelled by a deterministic relation depending on the distance R, the S-wave
 259 speed V_s and the latent period T_w :

$$\Delta T = \frac{R}{V_s} - T_w \quad (7)$$

260 T_w corresponds to the time necessary for the system to estimate the earthquake parameters. We
 261 assumed: $T_w = 4$ s and $V_s = 4$ km/s.

262 The loss module in Figure 3 is the part of the Bayesian network containing the indicators that were
 263 chosen for this study. The indicator related to the cost of risk management, CRM, is easily computed:
 264 either the system is installed, and the cost is C, or it is not installed, and the cost is 0:

$$\begin{cases} CRM = 0 & \text{if } P_c = 1 \\ CRM = C & \text{if } P_c < 1 \end{cases} \quad (8)$$

265 In this study, the cost C was arbitrarily chosen to be 500 000€ per year. The two other indicators
 266 depend on the performance of the system. For each event, there are four possible outcomes, which
 267 are summarised in Table 1.

268 False alarms correspond to Type I errors, when the barrier is lowered while the event was not strong
 269 enough to create significant damage on the bridge. The indicator related to false alarms FA, is thus
 270 computed with the following relationship after each event (recalling that we are considering a period
 271 of 50 years and we are interested in the number of false alarms in five-year intervals):

$$\text{After each event } i: \begin{cases} fa_i = 1 & \text{if } A = 1 \text{ and } DS < DS3 \\ fa_i = 0 & \text{otherwise} \end{cases} \quad (9)$$

$$FA = \sum_{i=1}^N fa_i / 10$$

272 With N being the total number of earthquakes that happened during the chosen time horizon.

273 For the computation of the indicator VaR (see Taillefer *et al.*, 2014), the number of vehicles at risk,
 274 these new parameters are introduced:

- 275 - L: length of the bridge (km);
- 276 - Q: average flow of vehicles on the bridge (number/hour); and
- 277 - V: average speed of the vehicles on the bridge (km/h).

278 Following the initial definition of VaR, when DS3 is not reached, there are no vehicles at risk. If there
 279 is a missed alarm (False Negative case), then all the vehicles on the bridge are at risk. If there is a
 280 True Positive, then this number of vehicles can leave the bridge during ΔT :

$$\text{after each event } i: \begin{cases} var_i = 0, & \text{if } DS < DS3 \\ var_i = \frac{Q \times L}{V}, & \text{if } DS \geq 3 \text{ and } A = 0 \\ var_i = \frac{Q \times L}{V} - Q \times \Delta T, & \text{if } DS \geq 3 \text{ and } A = 1 \end{cases} \quad (10)$$

$$VaR = \sum_{i=1}^N var_i$$

281 For this case study, we assumed: L = 1 km; Q = 4167 vehicles/h (i.e. 100 000 vehicles/day); and
 282 V = 70 km/h.

283 The decision-making model is thus completed. With the Bayesian network, each indicator can be
 284 computed for each alternative (i.e. a given value of P_C).

285 4.2. Application of MAUT

286 Once the indicators are computed, the MAUT is used to combine them in a unique quantitative
 287 indicator, called the utility u . A global utility function or score function is thus defined as:

$$u_{global} = f(VaR, FA, CRM)$$

288 To assess the applicability of the method to our case study, we considered four hypothetical decision
289 makers (DMs) leading to four different utility functions. Following the process detailed by Keeney
290 and Raiffa (1993), each decision maker was asked to answer a guided questionnaire that was
291 constructed to elicit preferences and to weight each indicator in comparison to the others. The main
292 result is the utility function but the process is designed in a way that the main hypotheses of the
293 theory are checked, as well as the coherency of the answers of the DMs. As an example, a typical
294 question that can be asked in the guided questionnaire would be: “Would you rather play a lottery
295 where you have a 50% chance of winning 100€ or nothing, or would you rather have 50€ (sure
296 value)?”

297 4.3. Description of the process

298 The elicitation process is described here for one DM. For the others, only the results are shown. Le
299 Guenan et al. (2014) present details for the other DMs.

300 The first step in the process is to determine the ranges of possible values for each of the three
301 indicators that are used (Table 2). Preliminary simulations of the Bayesian network helped assess
302 these ranges.

303 The next step, following Keeney and Raiffa (1993), is to check the relevant independence
304 assumptions between the indicators. These assumptions allow us to use simplified aggregated form
305 of the global utility function. Otherwise, the form can become too complicated and would require
306 simplification. In order to test the hypothesis, one of the indicators is fixed to a certain value, and the
307 DM is asked for preferences between lotteries and fixed values regarding another indicator. Then the
308 value of the first indicator is changed and the DM is asked the same questions regarding the other
309 indicator. If the answers are the same, the second indicator is said to be *utility independent* from the
310 first indicator. The follow-up step is to confirm the form of the utility function as multiplicative or
311 additive. To do so, the DM is asked to choose between two lotteries: $\langle (\text{VaR} = 20; \text{FA} = 0); (\text{VaR} = 120;$
312 $\text{FA} = 5) \rangle^3$ or $\langle (\text{VaR} = 20; \text{FA} = 5); (\text{VaR} = 120; \text{FA} = 0) \rangle$. The first lottery corresponds to the additive
313 form, while the second corresponds to the multiplicative form. The DM chose the second lottery on
314 the basis that the first lottery could lead to a worse result. In the second lottery there is a
315 compensatory effect between the number of vehicles at risk and the number of false alarms. The
316 score function is thus (Keeney and Raiffa, 1993):

³ The notation $\langle X; Y \rangle$ designates lotteries with outcomes X or Y each with a 50% probability.

$$\begin{aligned}
& 1 + k \times u(VaR, FA, CRM) \\
& = [1 + k \times k_{VaR} \times u_{VaR}(VaR)] \\
& \quad \times [1 + k \times k_{FA} \times u_{FA}(FA)] \\
& \quad \times [1 + k \times k_{CRM} \times u_{CRM}(CRM)]
\end{aligned} \tag{11}$$

317 The next step is hence to determine the individual utility functions: $u_{X_i}(X_i)$.

318 We describe the process for the VaR indicator. The DM was first asked to confirm that the individual
319 utility function is monotonically decreasing: low values of VaR correspond to high values of utility and
320 vice-versa. Then, the preferences of the person between the lottery <0; 120> and the sure value of
321 60 were investigated. The DM, who showed a risk-averse behaviour, chose the sure value in order to
322 avoid the worst outcome of 120 VaR. Repeating the same process, for various values of x and h, the
323 DM had to choose between lotteries <x-h; x+h> and the sure value x. This confirmed the risk aversion
324 behaviour, with a slightly increasing tendency (i.e. the DM was shown to be more risk averse for high
325 values of VaR than for low values of VaR). The points of the utility function are then captured by
326 asking what the certainty equivalents of various lotteries are. The certainty equivalent of a given
327 lottery is the sure value reached when the DM cannot state a preference between the lottery and
328 the sure value. Results are shown in Table 3.

329 An exponential form equation is then used to fit the points obtained. Exponential forms, e.g.
330 $1 + b(1 - e^{a \times VaR})$ where a and b are positive constants, are appropriate for modelling constant risk
331 aversion functions or increasing risk aversion functions (Keeney and Raiffa, 1993). Other functions
332 could be used to fit the points, however. It was verified that the choice of the form of the function
333 has negligible impact on results. The parameters were adjusted manually to fit the points (Figure 8):

$$u_{VaR}(VaR) = 1 + 0.431 \times (1 - e^{VaR \times 0.01}); \text{ for } VaR \in [0; 120] \tag{12}$$

334 According to Keeney and Raiffa (1993), a limited number (typically five) of consistent points is
335 generally sufficient to evaluate the utility functions. The model was then validated by asking the DM
336 to give certainty equivalents of other lotteries.

337 For FA, the DM judged that a maximum of five false alarms per year were still a reasonable number
338 of interruptions. Consequently he chose a risk neutral attitude that led to a linear expression for the
339 utility:

$$\begin{cases} u_{FA}(FA) = 1 - \frac{FA}{5}; \text{ for } FA \in [0; 5] \\ u_{FA}(FA) = 0; \text{ for } FA > 5 \end{cases} \tag{13}$$

340 It was decided to avoid negative values and to consider that if the number of false alarms surpasses
341 five, then the utility is still null. For CRM, the indicator is binary, hence the utility function is:

$$\begin{cases} u_{CRM}(C) = 0 \\ u_{CRM}(0) = 1 \end{cases} \quad (14)$$

342 Those three individual utility functions should then be aggregated in the form of equation (11).
 343 Further questions are then asked to the DM to determine k , k_{VaR} , k_{FA} and k_{CRM} . Prior to quantitative
 344 investigations, the DM is asked to express his preferences for several situations (Table 4). For each
 345 situation, the DM always preferred option A. In the first two situations, the most important aspect
 346 for the DM was to keep the VaR to a minimum. In the third situation, he privileged a reduction of
 347 false alarms over the cost of the system. From these results it can be deduced that:

$$k_{VaR} > k_{FA} > k_{CRM} \quad (15)$$

348 In order to quantitatively assess the constants, the decision-maker is asked to choose between the
 349 options summarised in Table 5.

350 For $p = 10\%$, the DM chose Option B. For $p = 99\%$, the DM chose Option A. By progressing step by
 351 step, the DM was not able to state a preference between the two options with $p = 92\%$. It is thus
 352 possible to evaluate k_{VaR} by first noticing that:

$$u(VaR = 0; FA = 0; CRM = 0) = 1 \quad (16)$$

$$u(VaR = 120; FA = 5; CRM = 500) = 0 \quad (17)$$

353 Hence, the result of the situation of Table 5 is:

$$p \times 1 + (1 - p) \times 0 = u(VaR = 0; FA = 5; CRM = 500) \quad (18)$$

$$u(VaR = 0; FA = 5; CRM = 500) = p \quad (19)$$

354 By substituting the result of (19) in (11), knowing the individual utility functions (12), (13) and (14),
 355 we can thus write:

$$1 + k \times p = [1 + k \times k_{VaR} \times 1] \times [1 + k \times k_{FA} \times 0] \times [1 + k \times k_{CRM} \times 0] \quad (20)$$

$$1 + k \times p = 1 + k \times k_{VaR} \quad (21)$$

356 Hence: $k_{VaR} = 0.92$. The same process was used to estimate $k_{FA} = 0.18$ and $k_{CRM} = 0.02$.

357 To evaluate k , we then need to solve the following second-degree polynomial equation:

$$1 + k \times 1 = [1 + k \times k_{VaR} \times 1] \times [1 + k \times k_{FA} \times 1] \times [1 + k \times k_{CRM} \times 1] \quad (22)$$

358 We obtained $k = -0.65$. k is negative which is in good agreement with the observation that the person
 359 preferred a lottery with compensative effects.

360 In summary, the global utility function is (see Figure 9 for a graphical representation of this function):

$$\begin{aligned} & u(VaR, FA, CRM) \\ & = \frac{[1 + k \times k_{VaR} \times u_{VaR}(VaR)] \times [1 + k \times k_{FA} \times u_{FA}(FA)] \times [1 + k \times k_{CRM} \times u_{CRM}(CRM)] - 1}{k} \end{aligned} \quad (23)$$

361 The same process was repeated for three other DMs, with the following results (see Table 6). It can
362 be noted in Table 6 that DM n°4 is the only DM that is not risk neutral towards false alarms. He
363 actually shows a risk-prone attitude because he considered that the values are low enough to prefer
364 lotteries rather than the certainty equivalents.

365 5. Results

366 The combination of the Bayesian network and the MAUT allows computation of a global utility for
367 various P_C . The main result is shown in Figure 10.

368 The utility function of two of the DMs, DM n°1 and DM n°3, have a maximum that corresponds to a
369 P_C different than 1. This means that for them, the optimal solution is to implement the EEWS and the
370 main parameter that will influence how the system behaves is the P_C corresponding to the maximum
371 in the utility function. For instance for DM n°1, the best setting would be $P_C = 0.05$ (Figure 11).

372 On the other hand, the P_C that maximizes the utility for the other two DMs (DM n°2 and DM n°4) is 1,
373 corresponding to not installing the EEWS. It appears that for them, the benefits brought by the
374 system are not large enough to overcome the resulting costs of false alarms and the installation and
375 operational costs of running the system. For instance, the utility function of DM n°4 is shown in
376 Figure 12.

377 These results show that the method allows not only to find the best threshold but also to evaluate
378 whether the planned mitigation action actually improves the situation with respect to 'business as
379 usual'.

380 6. Discussions

381 It is interesting to see the respective contributions of the utility of VaR versus the utility of FA (Figure
382 13 and Figure 14). U_{VaR} logically decreases as the warning threshold increases: the lower the
383 threshold, the more sensitive the system, the lower the number of vehicles at risk and thus the
384 higher the utility. Results are similar from one DM to another. The functions slightly decrease for
385 refined settings, which means that below a certain level ($\sim 10^{-3}$), improving the sensitivity has a
386 limited impact on reducing the number of vehicles at risk. The individual utility is around 0.87, which
387 is because most simulations yield zero VaR due to the absence of earthquakes. Above 10^{-2} , the slope
388 of u_{VaR} is higher: the setting has a large influence on the utility, which is because the number of
389 missed alarms increases. U_{VaR} values never decrease below 0.83, even if there is no EEWS. It should
390 also be noticed that we decided to consider the number of VaR for each 50-year horizon, and to
391 assign the maximum utility to u_{VaR} in the absence of earthquakes. Since the return period of

392 damaging earthquakes in the simulation is around 125 years, two thirds of simulations have
393 maximum utilities, not because of a perfectly functioning EEWs but because of the absence of
394 earthquakes.

395 U_{FA} varies in the opposite sense to u_{VaR} : when the system is very sensitive, the number of false alarms
396 is higher, and thus the utility lower. For very small warning thresholds (below 10^{-6}), the slope is very
397 flat with utility close to null, which corresponds to more than five alarms per five-year period. The
398 slope then becomes very steep for utilities near unity because for a warning threshold of unity (the
399 barrier never lowers) there is no false alarm. Even for the risk-prone DM, the individual utility
400 function of FA is not significantly modified.

401 So while the individual utility functions do not vary much from one DM to other, the final results are
402 quite different. It appears then that the main factor controlling the results is the relative weights
403 given to these utility functions. A graph comparing those weights is shown in Figure 15.

404 Even if all DMs agree that VaR should have the highest weight (between 0.8 and 0.97), the
405 importance of the two other indicators is very different: a factor 40 between the lowest and the
406 highest values of FA; and a factor 20 for CRM. For k , which measures the level of interaction
407 (compensation effects) between parameters, it can also be seen that we obtain very different values;
408 but since k is obtained by solving an equation that is directly dependent on three other highly-
409 uncertain constants, it would be difficult to reach conclusions on this value. To explain such
410 discrepancies, we assume that the weights do not only measure each DM's preferences, but also
411 reveal the assumptions that each DM formulated to complete the questionnaire. It would be
412 interesting to carry out the same analysis with an actual problem, involving real stakeholders, to be
413 able to distinguish which differences come from preferences and which ones arise from the fictional
414 context.

415 It should be remembered that the DMs for this case study were, in fact, BRGM staff and not real
416 bridge managers. Therefore, their perceptions of risks versus costs were probably not comparable to
417 those of real DMs for such a situation. In addition, the same DM may answer differently on another
418 day or his interpretation of probabilities is biased so his answers do not reflect what his real
419 preferences are. In order to overcome this, we suggest that the process of MAUT is used as a basis
420 for discussions, between the analyst, the main DM, and risk management experts. The most
421 important aspect is the respective weights of the k_i .

422 To determine the weights in the global utility function, the DM is explicitly asked his preferences by
423 comparing the different indicators.

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- VaR was easier to handle than human lives because of two things: the indicator was relatively easy to compute, and it was easy for the DM to appreciate: it is easy to imagine a car on a bridge during an earthquake, and it is not difficult to imagine the consequences. The main problem is that making a rational decision when human lives are at stake often proves difficult, as most decision makers in those case will not tolerate any trade-off.
 - We chose DS3 rather than DS5 in the definition of VaR because DS5 was a very rare event in this case study. This poses two problems. Firstly, a computational problem because of the way the Bayesian network works by performing Monte Carlo sampling. In order to catch rare events, the number of samples must be very high and so the computational time to solve the problem becomes long. The second issue is that it was difficult to create a useful utility function based on an indicator whose expected value is very close to null.
 - In the same way, it took several attempts before the indicator related to false alarms was fixed to the number of false alarms per five-year interval. False alarms may occur several times per year, and it is easier to make projections for a short-term horizon than for 50 years. In addition, using a shorter time horizon enables taking into account the fact that the decision maker may not be indifferent between one false alarm every five years during 50 years and ten FAs during one year and none the other 49 years.
 - Lastly, we used an arbitrary value of CRM, but we did not try the same exercise with different values. We believe that the value of the various weights have more influence on the results than the actual figure, but this would require further testing in order to be certain of this assumption.

445

446 7. Conclusions

447 In this article, we have proposed an approach to help overcome one of the outstanding obstacles to
448 wider consideration of EEWS as a possible element of a seismic risk-reduction programme. Namely,
449 how can different views on acceptable risk be taken into account when deciding whether an EEWS is
450 appropriate for a given application? and, if it is beneficial, how can the threshold to trigger an action
451 be fixed taking account of its 'costs' and 'benefits' (in the widest sense and not simply in terms of
452 monetary value)? The method was based on the combination of multi-attribute utility theory and a
453 Bayesian network for earthquake loss assessment. This procedure could be a useful component of
454 the wider framework for participatory decision making that is also proposed here. A participatory
455 viewpoint is necessary in the case of EEWS because such systems can affect/and be affected by many
456 different groups, e.g. infrastructure owners, elected officials and the local population. We believe

457 that the approach outlined here has the potential to help EEWs fulfil their potential as a component
458 of operational earthquake risk reduction plans.

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464 **References**

- 465 Akkar, S. and Bommer, J. J. (2010), Empirical equations for the prediction of PGA, PGV and spectral
466 accelerations in Europe, the Mediterranean region and the Middle East, *Seismological Research*
467 *Letters*, **81**(2), 195–206.
- 468 Allen, R. M. (2011), Earthquakes, Early and Strong Motion Warning in *Encyclopedia of Solid Earth*
469 *Geophysics*, H. Gupta (ed), 226-233, Berlin and Heidelberg: Springer.
- 470 Allen, R. M. and Kanamori, H. (2003), The Potential for Earthquake Early Warning in Southern
471 California, *Science*, **300** (2003): 786.
- 472 Auclair, S., Goula, X., Jara, J.A. and Colom, Y. (2015), Feasibility and interest in earthquake early
473 warning systems for areas of moderate seismicity: Case study for the Pyrenees, *Pure and Applied*
474 *Geophysics*, DOI 10.1007/s00024-014-0957-x, in press.
- 475 Castelletti, A. and Soncini-Sessa, R. (2006), A procedural approach to strengthening integration and
476 participation in water resource planning, *Environmental Modelling and Software*, **21**(10), 1455–1470.
- 477 Cua, G., and Heaton, T. (2007), The Virtual Seismologist (VS) method: A Bayesian approach to
478 earthquake early warning in Earthquake Early Warning Systems, P. Gasparini, G. Manfredi, and J.
479 Zschau (ed), 97–132. Berlin and Heidelberg: Springer.
- 480 Douglas, J., Woo, G., Auclair, S. and Le Guenan, T. (2012), Critical review of participatory decision
481 making in fields other than earthquake risk reduction. Report BRGM/RP-61480-FR. Available online
482 at: <http://www.brgm.eu/content/public-reports>.
- 483 FEMA, (2003) Multi-hazard loss estimation Earthquake Model HAZUS-MH MR3 Technical Manual.
- 484 Giardini D., J. Woessner, L. Danciu, H. Crowley, F. Cotton, G. Grünthal, R. Pinho, G. Valensise, S.
485 Akkar, R. Arvidsson, R. Basili, T. Cameelbeeck, A. Campos-Costa, J. Douglas, M. B. Demircioglu, M.

486 Erdik, J. Fonseca, B. Glavatovic, C. Lindholm, K. Makropoulos, F. Meletti, R. Musson, K. Pitilakis, K.
487 Sesetyan, D. Stromeyer, M. Stucchi, A. Rovida, (2013) Seismic Hazard Harmonization in Europe
488 (SHARE): Online Data Resource, doi: 10.12686/SED-00000001-SHARE, 2013.

489 Iervolino, I., Massimiliano, G. and Manfredi, G. (2007), Expected Loss-based Alarm Threshold Set for
490 Earthquake Early Warning Systems, *Earthquake Engineering and Structural Dynamics*, **36**(9), 1151–
491 1168. DOI: 10.1002/eqe.675.

492 Iervolino, I., Giorgio, M., Galasso, C., Manfredi, G. (2009), Uncertainty in early warning predictions of
493 engineering ground motion parameters: What really matters? *Geophysical Research Letters*, **36**(5),
494 DOI: 10.1029/2008GL036644.

495 Kailiponi, P. (2010), Analysing evacuation decisions using multi-attribute utility theory (MAUT),
496 *Procedia Engineering*, **3**, 163-174. DOI: 10.1016/j.proeng.2010.07.016.

497 Keeney, R. L. and Raiffa, H. (1993), *Decisions with multiple objectives: Preferences and value*
498 *tradeoffs*, John Wiley and Sons, New York, New York, USA.

499 Le Guenan, T., Smal, F., Loschetter, A., Auclair, S. and Douglas, J. (2014), Proposed participatory
500 decision-making framework of REAKT and application to test cases, Deliverable D6.7, REAKT
501 (Strategies and tools for Real Time EArthquake RiSk ReducTion). Available online at:
502 <http://www.reaktproject.eu/deliverables/REAKT-D6.7.pdf>.

503 Neapolitan, R. E. (2004). *Learning bayesian networks* (Vol. 38). Upper Saddle River: Prentice Hall.

504 Satriano, C., Elia, L., Martino, C., Lancieri, M., Zollo, A. and Iannaccone, G. (2011), PRESTo, the
505 earthquake warning system for southern Italy: Concepts, capabilities and future perspectives, *Soil*
506 *Dynamics and Earthquake Engineering*, **31**(2), 137-153, DOI: 10.1016/j.soildyn.2010.06.008.

507 Taillefer, N., Monfort-Climent, D. and Bastone, V. (2014), Loss estimation for co-seismic risk
508 assessment through an EWS. Report BRGM/RP-63614-FR. Available online at:
509 <http://www.brgm.eu/content/public-reports>.

510 Von Neumann, J. and Morgenstern, O. (1953), *Theory of Games and Economic Behavior*, Princeton
511 University Press, Princeton, New Jersey, USA.

512 Wang, J. P., Wu, Y. M., Lin, T. L., Brant, L. (2012), The uncertainties of a PD36PGV onsite earthquake
513 early warning system, *Soil Dynamics and Earthquake Engineering*, **36**, 32-37.

514 Wu, S., Beck, J. L. and Heaton, T. H. (2013), ePAD: Earthquake probability-based automated decision-
515 making framework for earthquake early warning, *Computer-Aided Civil and Infrastructure*
516 *Engineering*, **28**, 737-752.

517 Wurman, G., Allen, R. M. and Lombard, P. (2007), Toward earthquake early warning in northern
518 California, *Journal of Geophysical Research*, **112**, B08311, doi:10.1029/2006JB004830.

519 Zollo, A., Amoroso, O., Lancieri, M., Wu, Y. M., Kanamori, H. (2010), A threshold-based earthquake
520 early warning using dense accelerometer networks, *Geophysical Journal International*, **183**, 963-974.

521

522 **Tables**

523 **Table 1 : Classification of outcomes after each event**

	DS ≥ DS3	DS < DS3
A = 1: Barrier lowered	Correct outcome: True Positive (TP)	Type I error: False Positive (FP)
A = 0: Barrier not lowered	Type II error: False Negative (FN)	Correct outcome: True Negative (TN)

524

525 **Table 2 : Ranges of possible values for the three indicators**

Indicators	VaR: Number of vehicles at risk (for 50 years)	FA: Number of false alerts (per five years)	CRM: Annual cost of Risk Management (in k€)
Most preferred	0	0	0
Least preferred	120	5	500

526

527 **Table 3: Quantitative assessment of the individual utility function for VaR.**

Lottery	Certainty equivalent	Meaning		VaR	$U_{VaR}(VaR)$
<0,120>	75	$U_{VaR}(75) = 0.5$	→	0	1
<0,75>	43	$U_{VaR}(43) = 0.75$		43	0.75
<75,120>	100	$U_{VaR}(100) = 0.25$		75	0.5
Consistency check				100	0.25
<43,100>	X	$U_{VaR}(X) = 0.5$		120	0

528

529 **Table 4 : Questionnaire for hierarchizing the indicators**

Option A	Option B
VaR = 0; FA = 5; CRM = 500	VaR = 120; FA = 0; CRM = 500
VaR = 0; FA = 5; CRM = 500	VaR = 120; FA = 5; CRM = 0
VaR = 120; FA = 0; CRM = 500	VaR = 120; FA = 5; CRM = 0

530

531

532 **Table 5: Questionnaire for evaluating k_{VaR}**

Option A	Option B
$\langle (VaR = 0; FA = 0; CRM = 0); (VaR = 120; FA = 5; CRM = 500); p \rangle^4$	$VaR = 0; FA = 5; CRM = 500$

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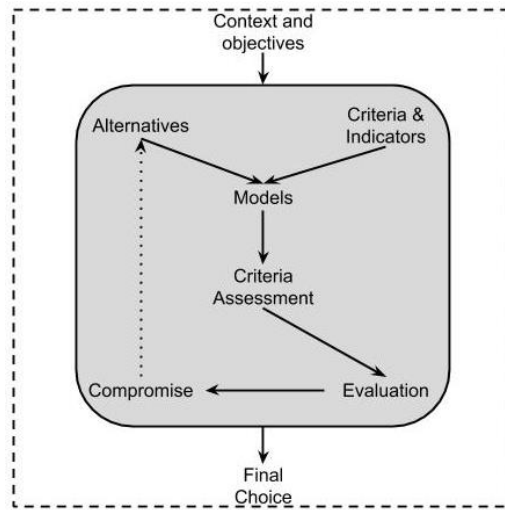
534 **Table 6 : Coefficients of the score function obtained for each DM**

Coefficients	DM n°1	DM n°2	DM n°3	DM n°4
k	-0.650	-0.066	-0.340	-0.870
k_{VaR}	0.92	0.84	0.97	0.80
k_{FA}	0.18	0.08	0.01	0.40
k_{CRM}	0.02	0.09	0.035	0.40
$u_{VaR}(VaR)$ for $VaR \in [0;120]$	$1+0.431 \times (1-e^{-VaR \times 0.01})$	$1+0.564 \times (1-e^{-VaR \times 0.0095})$	$1+0.365 \times (1-e^{-VaR \times 0.011})$	$1+0.62 \times (1-e^{-VaR \times 0.008})$
$u_{FA}(FA)$ for $FA \in [0;5]$	$1-FA/5$	$1-FA/5$	$1-FA/5$	$0.055 \times (5-FA)^{1.8}$
$u_{CRM}(0)$	1	1	1	1
$u_{CRM}(C)$	0	0	0	0

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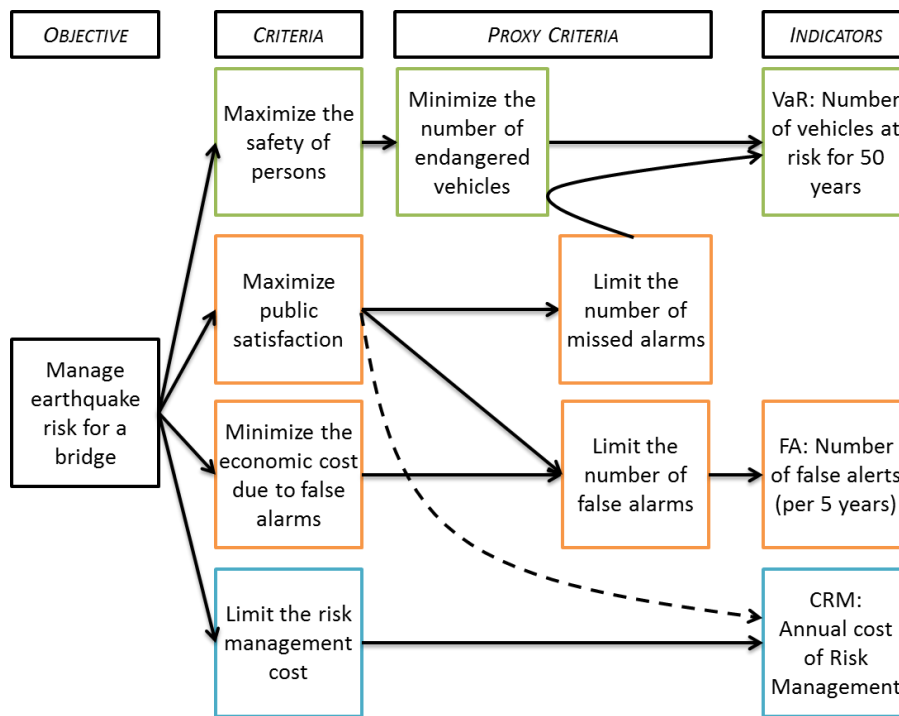
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⁴ The notation $\langle X;Y;P \rangle$ designates lotteries with outcomes X with probability P or Y with probability (1-P).



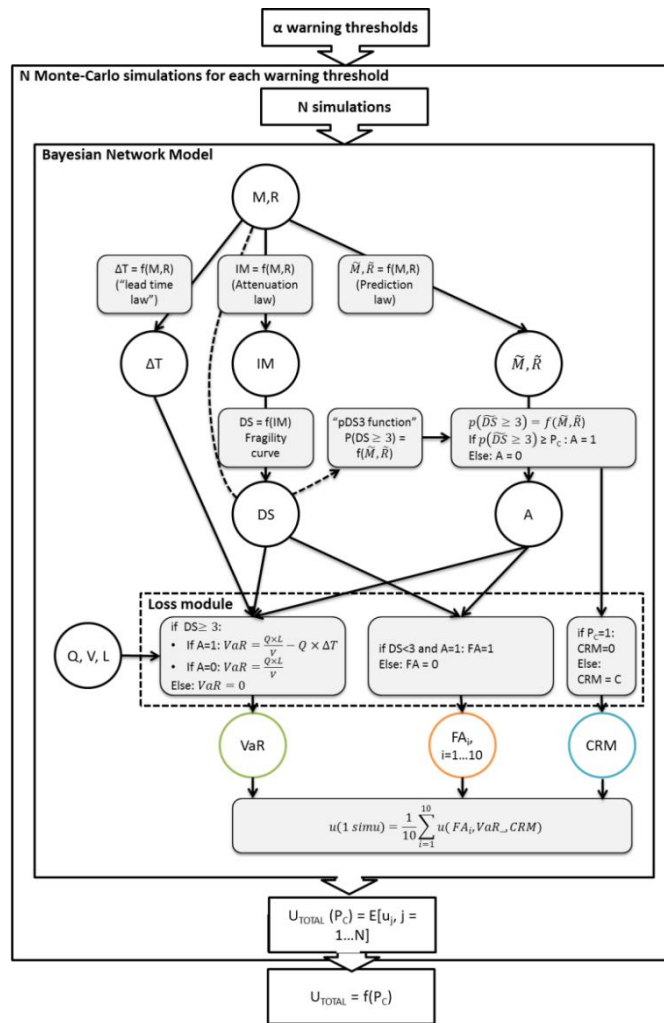
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539 **Figure 1: Proposed framework for participatory decision making in the context of EEW.**



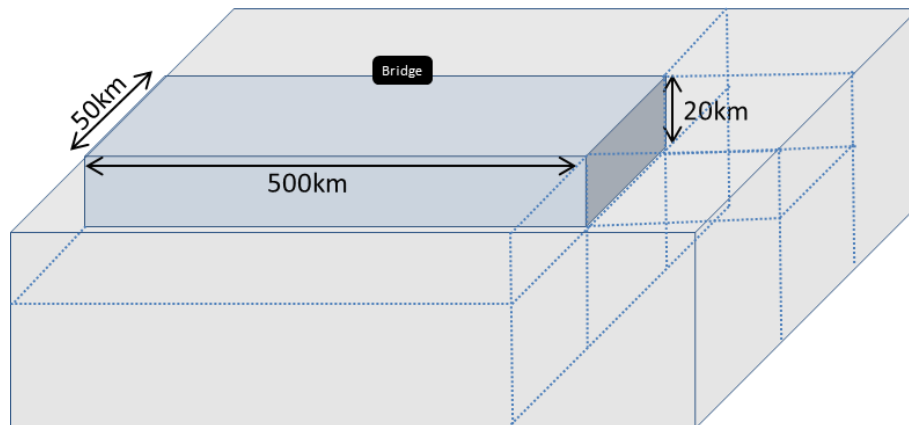
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541 **Figure 2 : Synthesis of the criteria and indicators defined for the case study.**



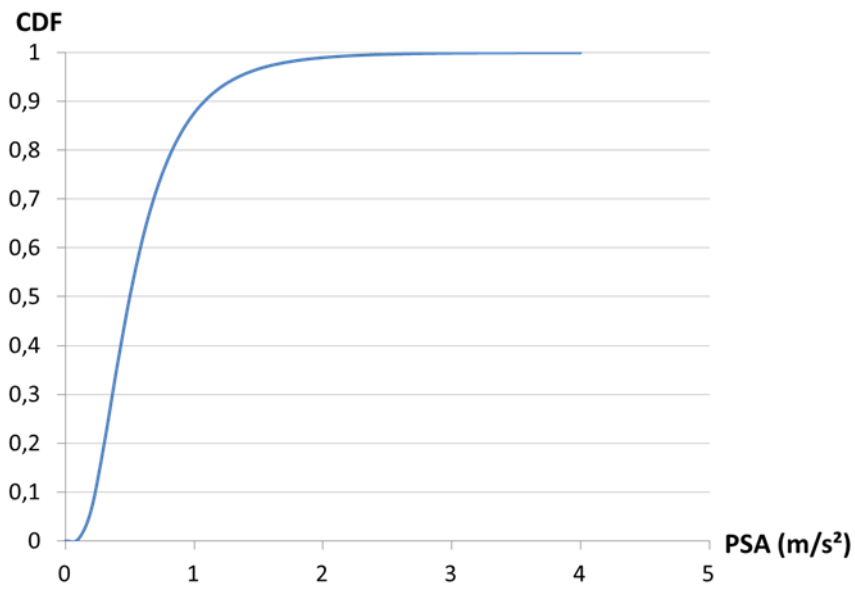
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543 Figure 3 : Bayesian network used for the case study.



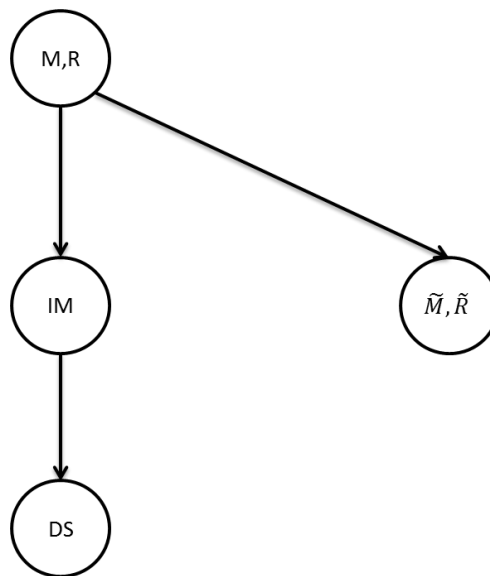
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545 Figure 4 : Diagram representing the seismicogenic zone and the location of the bridge.



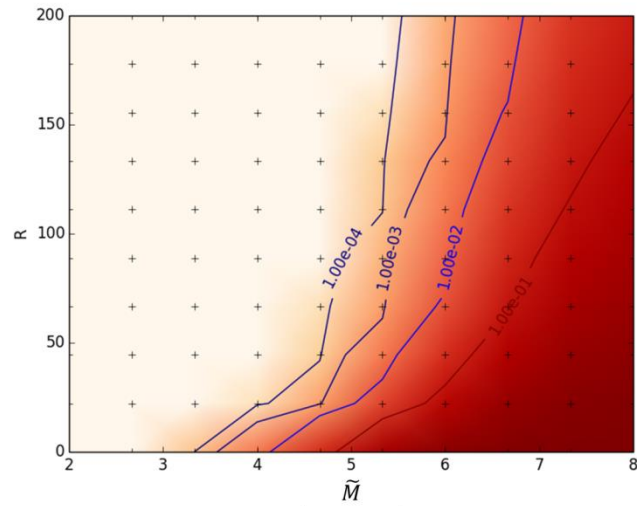
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547 Figure 5 : Fragility curve for the hypothetical bridge (corresponding to DS3) (PSA: peak spectral acceleration; CDF:
 548 cumulative distribution function)



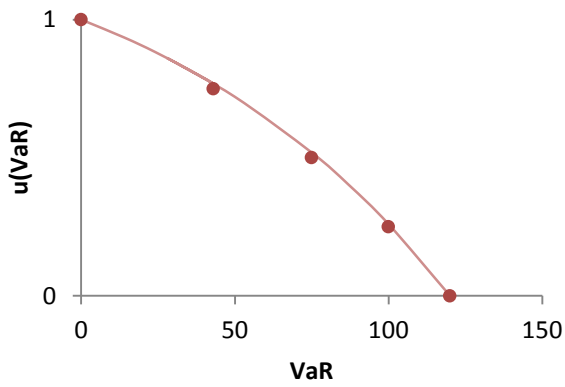
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550 Figure 6 : Subset of the Bayesian network.



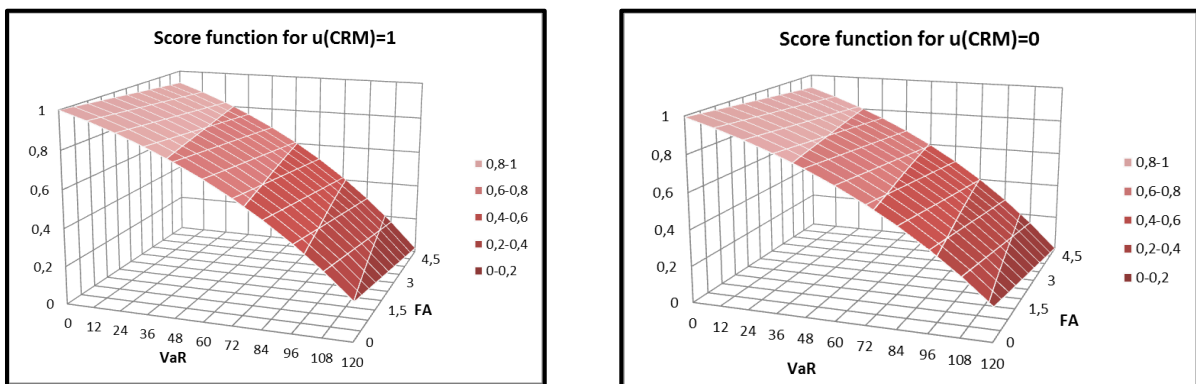
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552 **Figure 7 :** Graphical representation of $P(DS|\tilde{M}, \tilde{R})$.

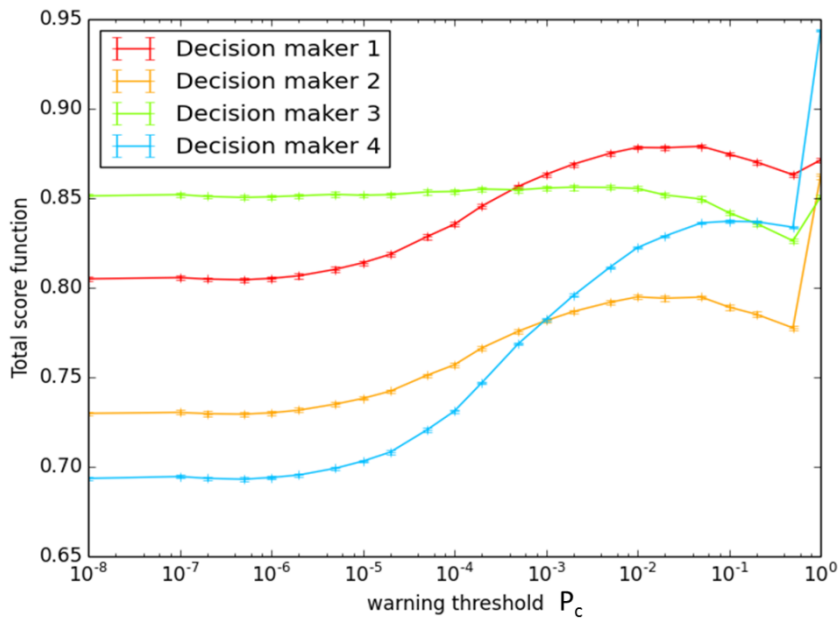


553 **Figure 8 :** Representation of the individual utility function of VaR. Left: Points captured. Right: Modelling by an
 554 exponential function.

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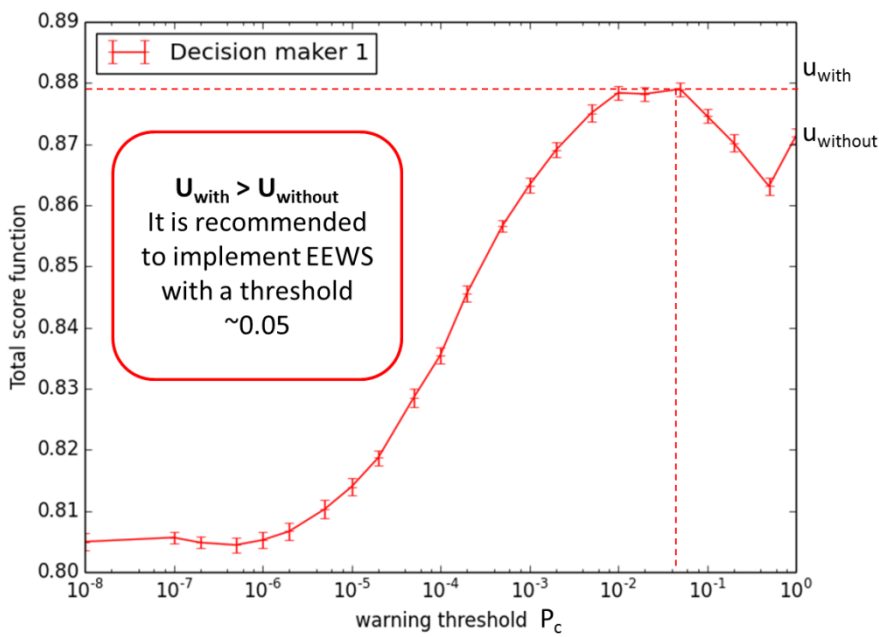


556 **Figure 9:** Graphical representation of the global utility function for DM n°1.



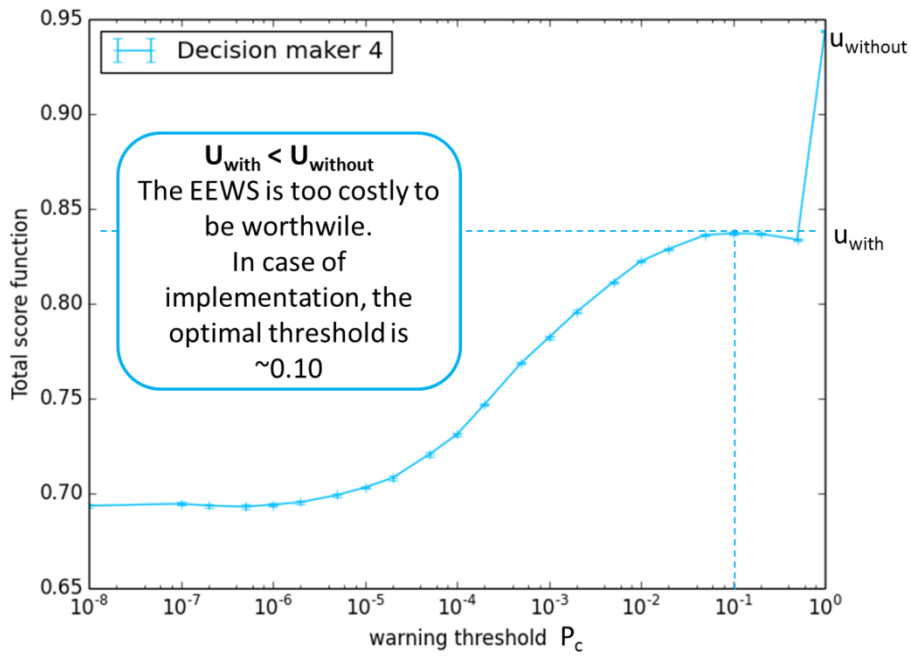
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558 Figure 10 : Expected value of the score function depending on the warning threshold, with preferences from the four
 559 DMs (error bars correspond to the 95% confidence intervals).



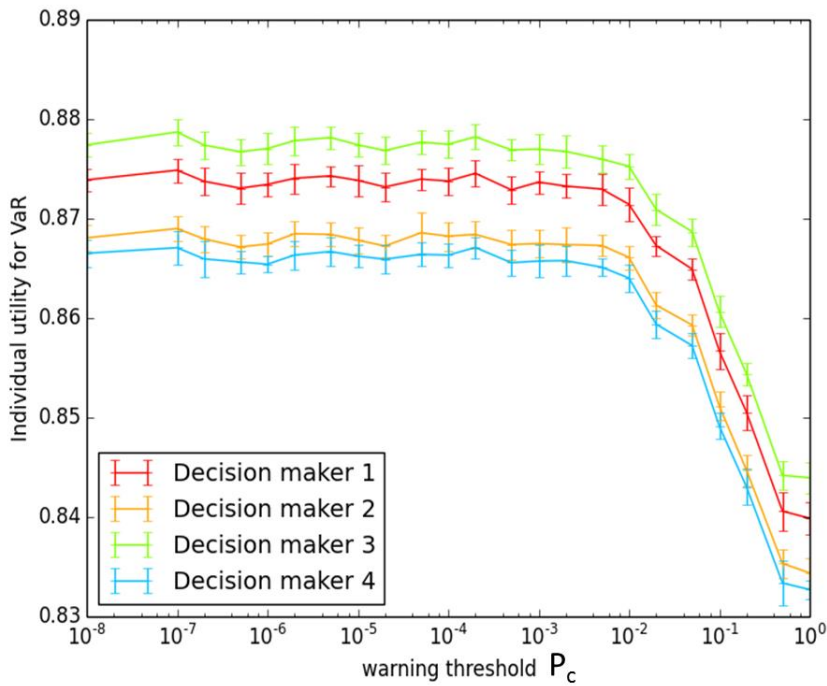
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561 Figure 11 : Expected value of the global utility function depending on the warning threshold for DM n°1.



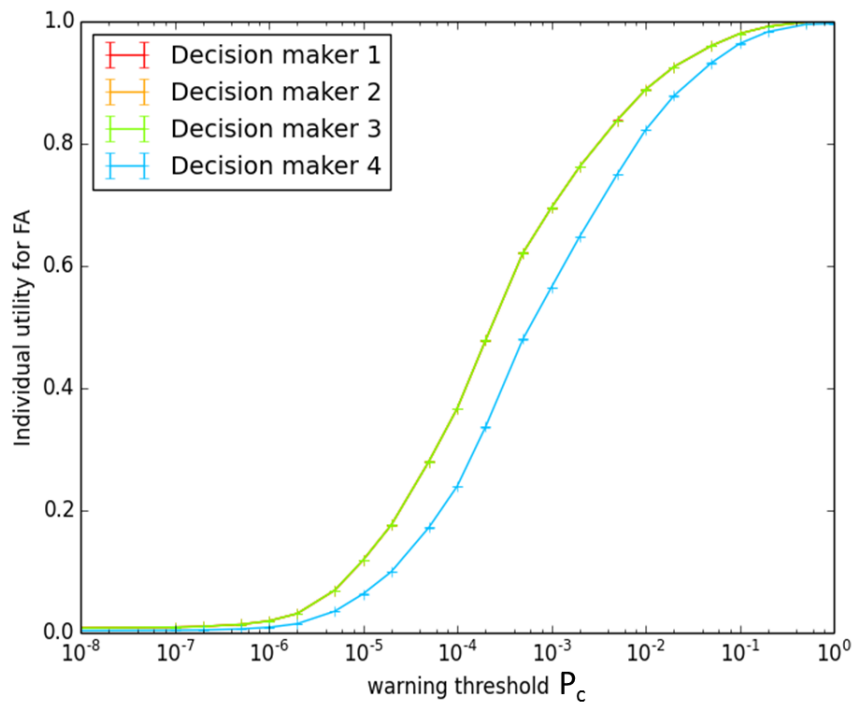
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563 Figure 12 : Expected value of the global utility function depending on the warning threshold for DM n°4.



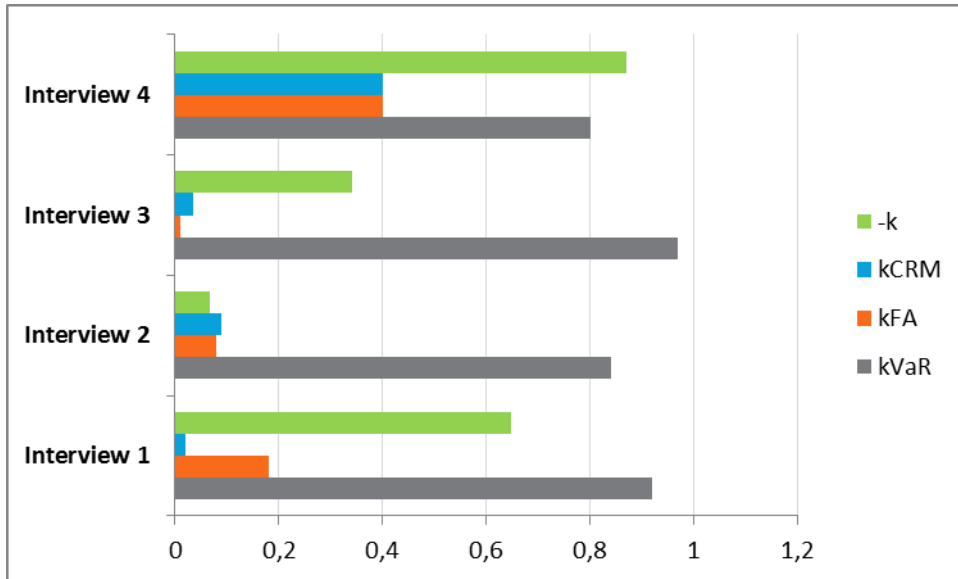
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565 Figure 13 : Expected value of U_{VaR} depending on the warning threshold, with preferences from the four DMs (error bars
566 correspond to the 95% confidence intervals).



567

568 Figure 14 : Expected value of U_{FA} depending on the warning threshold, with preferences from the four DMs. The first
 569 three curves are identical (Error bars correspond to the 95% confidence intervals).



570

571 Figure 15 : Comparison of the constants of the global utility function from the four interviews

572