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Accounting for end-user preferences in earthquake early warning systems

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Abstract*:*

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

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

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1. Introduction

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

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

There are various studies concerning the fixing of the appropriate threshold for EEWS using different mathematical approaches. For example, Zollo et al. (2010) propose to fix several thresholds within a two-parameter space (comprised of the average period of the P-wave signal and the peak displacement) but their approach is based on the hazard rather than by considering the potential losses connected with a potential risk-reduction action. On the other hand, Wang et al. (2012) develop an approach that does consider losses but the loss model is simple and user preferences are not taken into account when setting the threshold. Iervolino et al. (2007) use a more sophisticated loss model but again the preferences of the user are not considered. The recent proposal by Wu et al. (2013) for an ePAD system allows consideration of whether a user is risk averse (i.e. is biased towards taking fewer risks even if this means missing out on some rewards) but its application is only shown assuming risk neutrality. User preference is incorporated through a cost model determined by the user, which includes a model for the lead time as well. Constructing a cost model requires translating often vague preferences into actual numbers, which is not easy. In addition, because it is based on cost-benefit analysis (CBA) it requires costing everything, including the monetary value of a life saved. In addition, all these previous studies consider that the EEWS has already been installed.

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

2. Participatory decision making in EEW

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

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

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

2.1. Proposed framework

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

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

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

3. Multi-attribute utility theory

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

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

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

4. EEWS for a hypothetical bridge

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

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

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

To assess the 'barrier-lowering' action and to optimize its settings, the criteria or objectives of the EEWS must be defined. The first criterion is to reduce the seismic risk or "Maximize the safety of persons". This risk arises when there are vehicles on the bridge and there is a chance of the bridge being damaged by the earthquake. Consequently, a quantitative indicator corresponding to this criterion is the number of "vehicles at risk" defined as the number of vehicles on the bridge while the bridge is in a damage state higher or equal to DS3. This, however, cannot be the only objective or the consequence would be to always close the bridge as then the defined indicator would be certain to stay at null. Other objectives, linked to the service offered by the bridge must be added, i.e.: "Maximize public satisfaction" and "Minimize the economic cost due to false alarms". Both of these criteria were represented by the same indicator: the number of false alerts in a five-year interval (see following discussion for the rationale of this indicator). For our case study, a false alert means that the action was triggered but DS3 was not reached. A fourth criterion is defined corresponding to the desire to keep the cost of the EEWS to a minimum, i.e.: "Limit the risk management cost". This criterion is also needed as the efficiency of the system could be improved with infinite resources (allowing installation of an infinite amount of sensors, for example). The related quantitative indicator is, hence, the "Annual cost of Risk Management" and can be expressed as a percentage of the total budget for operating the bridge. A summary of the criteria and indicators for this case study are shown in Figure 2. Note that one indicator can represent several criteria or proxy-criteria. The annual cost of risk management also indirectly corresponds to “maximize public satisfaction” because if the cost is kept low then toll fees or taxes also remain low thereby satisfying the public. To “limit the number of missed alarms” means that the system should work as planned and hence should “minimize the number of endangered vehicles”. The VaR indicator also represents the proxy-criteria “limit the number of missed alarms”.

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

4.1. Bayesian network for loss assessment

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

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

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

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

The Damage State "DS" can then be computed using a fragility curve for the bridge: P(DS|IM). This curve is presented in Figure 5 (Taillefer et al., 2014).

This path, P(DS|IM) × P(IM|M,R) × P(M,R), simulates the effect of future earthquakes on the bridge. The other part of the Bayesian network simulates how the EEWS reacts to the earthquakes.

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

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

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

The node "A" represents the action taken by the system. It is a discrete variable: for A= 1, the action is performed; else A = 0 and the action is not performed. The action is defined using equation (1), but in the system, no real-time measurement of DS is made: only $\widetilde{M}$ and $\tilde{R}$ are estimated. Thus, we need to have a relationship in the form: $P(A|\widetilde{M}, \tilde{R})$. In order to determine this conditional probability, we first use a subset of the Bayesian network (see Figure 6), allowing us to compute $P\left(DS\middle|\widetilde{M},\tilde{R}\right)$. Using the properties of Bayesian networks (see e.g. Neapolitan, 2004 for more details), we can use the law of total probability and the Markov condition in order to obtain:

$$P\left(DS\middle|\widetilde{M},\tilde{R}\right) = \int\limits_{IM} P(DS|IM) \times P(IM|\widetilde{M},\tilde{R})dIM \tag{4}$$

$$P\left(DS\middle|\widetilde{M},\tilde{R}\right) = \iint\limits_{IM,M,R} (DS|IM) \times P(IM|M,R) \times P(M,R|\widetilde{M},\tilde{R})\, dIMdM,R \tag{5}$$

Applying the Bayes theorem:

$$P\left(M,R\middle|\widetilde{M},\tilde{R}\right) = \frac{P(\widetilde{M},\tilde{R}|M,R) \times P(M,R)}{\int_{M,R} P(\widetilde{M},\tilde{R}|M,R) \times P(M,R)} \tag{6}$$

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

The lead time "ΔT" is modelled by a deterministic relation depending on the distance R, the S-wave speed V_S and the latent period T_W:

$$\Delta T = \frac{R}{V_S} - T_w \tag{7}$$

T_W corresponds to the time necessary for the system to estimate the earthquake parameters. We assumed: T_W = 4 s and V_S = 4 km/s.

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

$$\begin{cases} CRM \;=\; 0 \text{ if } P_C = 1 \\ CRM \;=\; C \text{ if } P_C < 1 \end{cases} \tag{8}$$

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

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

$$\text{After each event } i\text{: } \begin{cases} fa_i = 1 \text{ if } A = 1 \text{ and } DS < DS3 \\ fa_i = 0 \text{ otherwise} \end{cases}$$
$$FA = \sum_{i=1}^{N} fa_i/10 \tag{9}$$

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

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

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

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

$$\text{after each event } i\text{: } \begin{cases} var_i = 0, \text{if } DS < DS3 \\ var_i = \dfrac{Q \times L}{V}, \text{if } DS \geq 3 \text{ and } A = 0 \\ var_i = \dfrac{Q \times L}{V} - Q \times \Delta T, \text{if } DS \geq 3 \text{ and } A = 1 \end{cases} \tag{10}$$
$$VaR = \sum_{i=1}^{N} var_i$$

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

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

4.2. Application of MAUT

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

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

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

4.3. Description of the process

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

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

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

[3] The notation <X; Y> designates lotteries with outcomes X or Y each with a 50% probability.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

5. Results

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

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

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, corresponding to not installing the EEWS. It appears that for them, the benefits brought by the system are not large enough to overcome the resulting costs of false alarms and the installation and operational costs of running the system. For instance, the utility function of DM n°4 is shown in Figure 12.

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

6. Discussions

It is interesting to see the respective contributions of the utility of VaR versus the utility of FA (Figure 13 and Figure 14). U_{VaR} logically decreases as the warning threshold increases: the lower the threshold, the more sensitive the system, the lower the number of vehicles at risk and thus the higher the utility. Results are similar from one DM to another. The functions slightly decrease for refined settings, which means that below a certain level (~10^{-3}), improving the sensitivity has a limited impact on reducing the number of vehicles at risk. The individual utility is around 0.87, which is because most simulations yield zero VaR due to the absence of earthquakes. Above 10^{-2}, the slope of u_{VaR} is higher: the setting has a large influence on the utility, which is because the number of missed alarms increases. U_{VaR} values never decrease below 0.83, even if there is no EEWS. It should also be noticed that we decided to consider the number of VaR for each 50-year horizon, and to assign the maximum utility to u_{VaR} in the absence of earthquakes. Since the return period of damaging earthquakes in the simulation is around 125 years, two thirds of simulations have maximum utilities, not because of a perfectly functioning EEWS but because of the absence of earthquakes.

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

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

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

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

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

- 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.

7. Conclusions

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

Acknowledgments

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Tables

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)

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

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

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

→

VaR	**U_{VaR}(VaR)**
0	1
43	0.75
75	0.5
100	0.25
120	0

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

Table 5: Questionnaire for evaluating k_{VaR}

Option A	Option B
<(VaR = 0; FA = 0; CRM = 0); (VaR = 120; FA = 5; CRM = 500); p>[4]	VaR = 0; FA = 5; CRM = 500

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

[4] The notation <X ;Y ;P> designates lotteries with outcomes X with probability P or Y with probability (1-P).

Figures

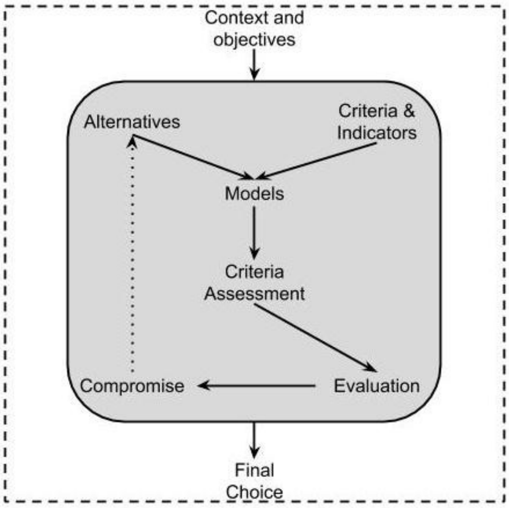

Figure 1: Proposed framework for participatory decision making in the context of EEW.

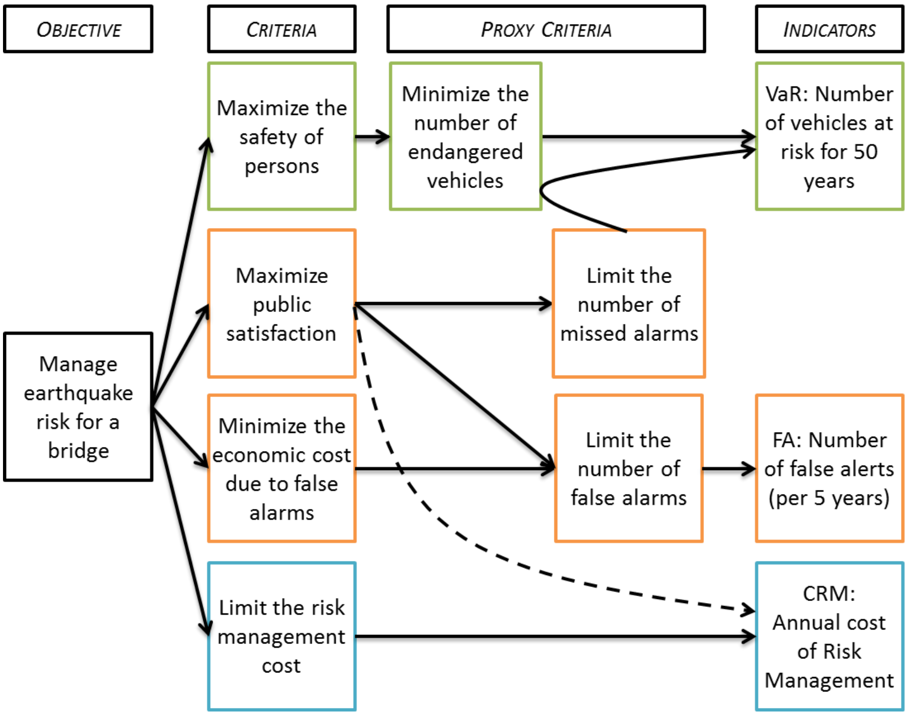

Figure 2 : Synthesis of the criteria and indicators defined for the case study.

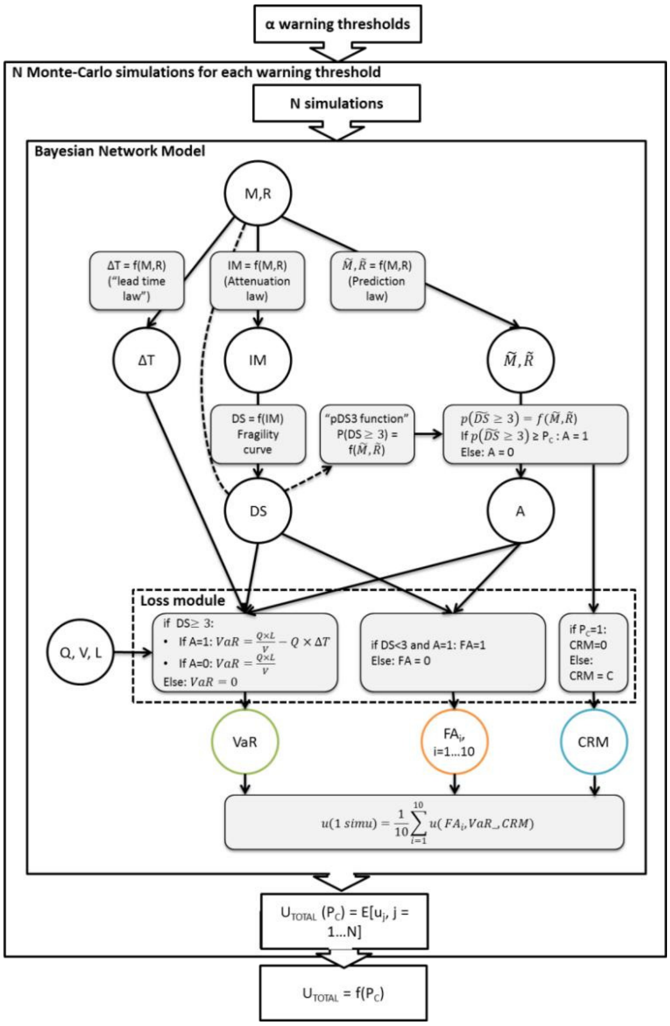

Figure 3 : Bayesian network used for the case study.

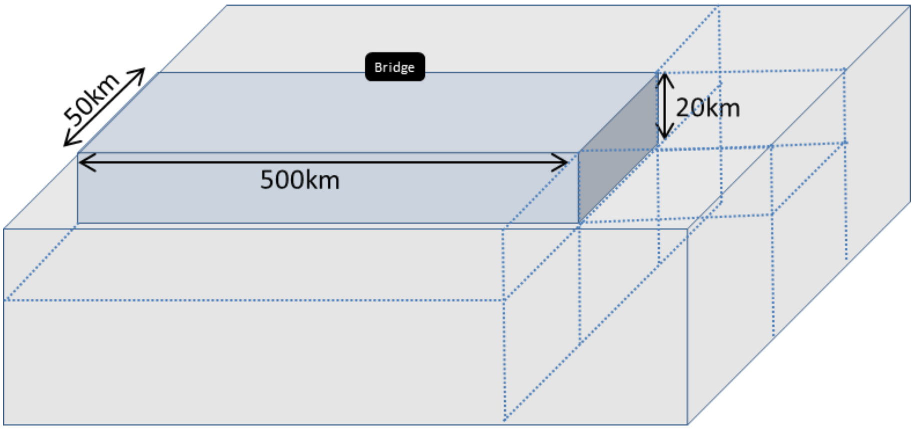

Figure 4 : Diagram representing the seismogenic zone and the location of the bridge.

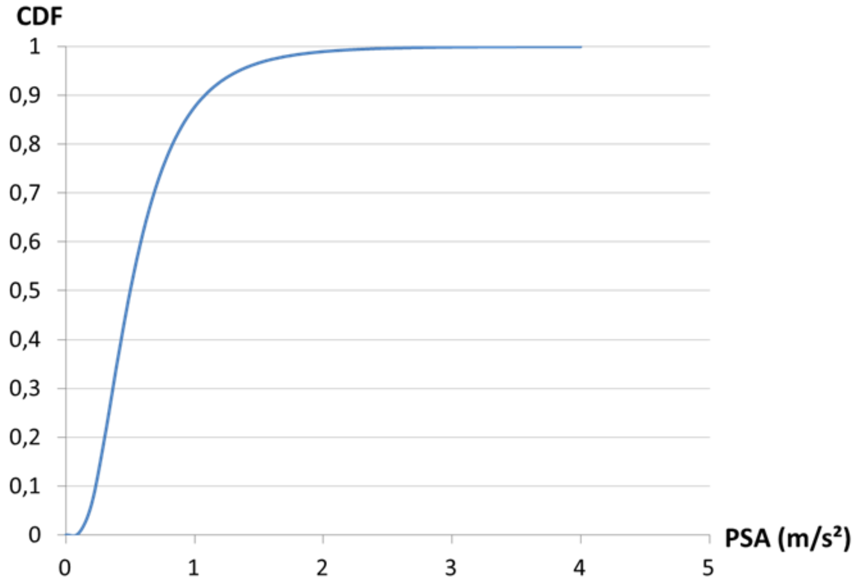

Figure 5 : Fragility curve for the hypothetical bridge (corresponding to DS3) (PSA: peak spectral acceleration; CDF: cumulative distribution function)

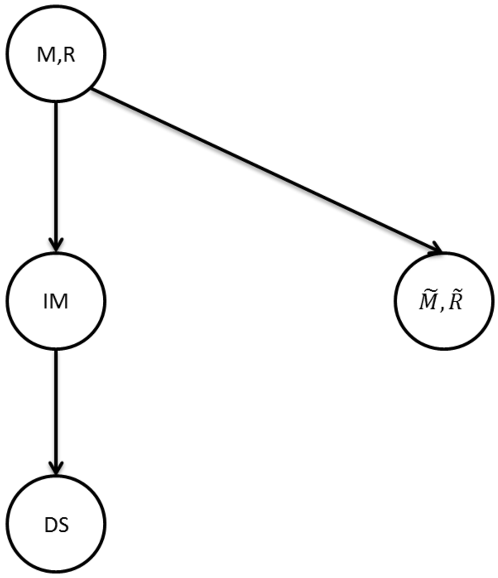

Figure 6 : Subset of the Bayesian network.

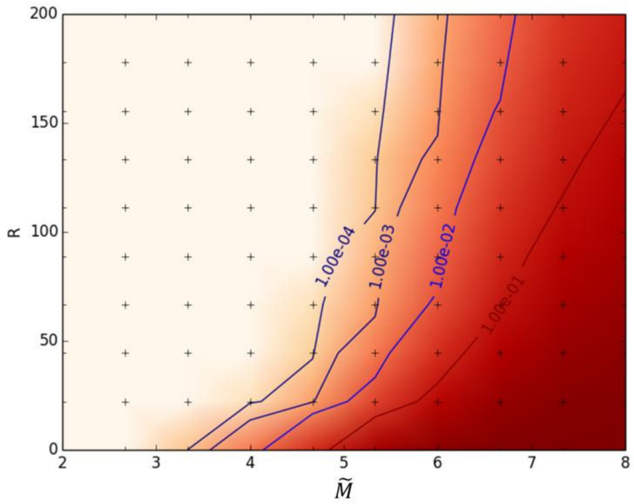

Figure 7 : Graphical representation of $P\left(DS\middle|\widetilde{M},\widetilde{R}\right)$.

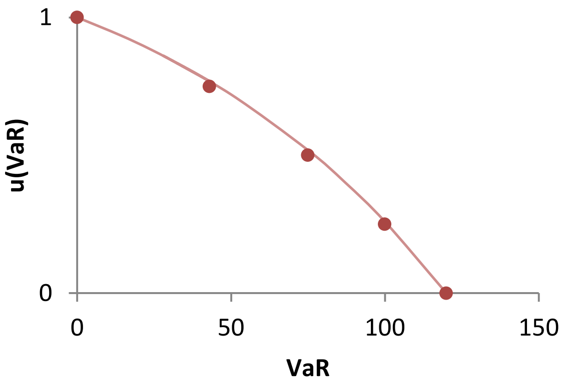

Figure 8 : Representation of the individual utility function of VaR. Left: Points captured. Right: Modelling by an exponential function.

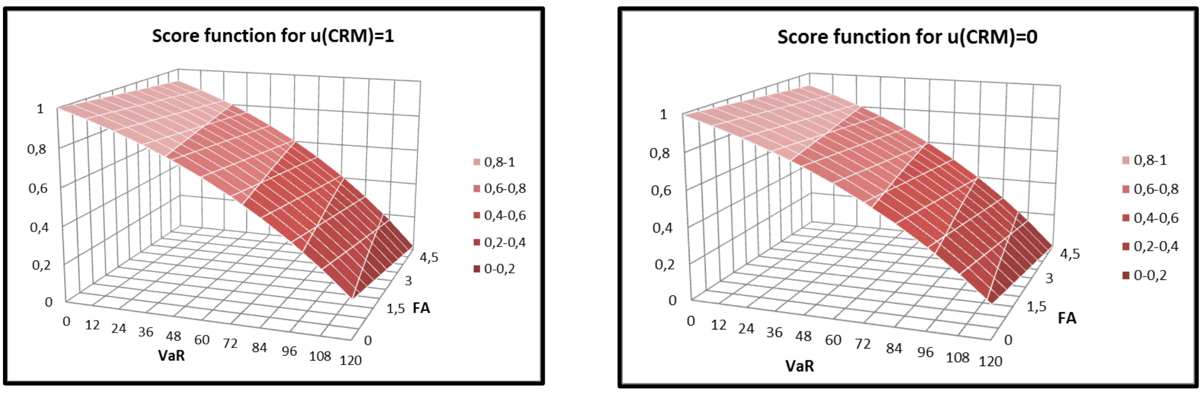

Figure 9: Graphical representation of the global utility function for DM n°1.

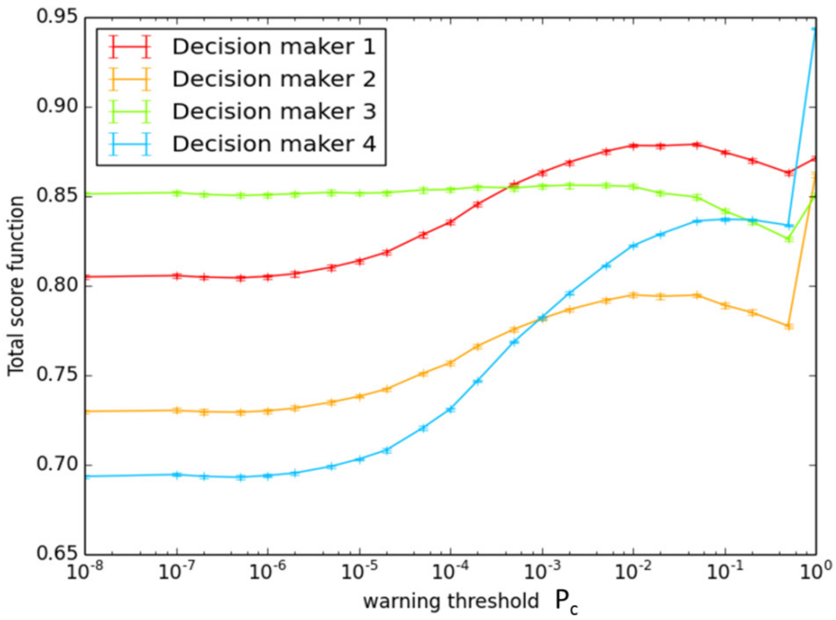

Figure 10 : Expected value of the score function depending on the warning threshold, with preferences from the four DMs (error bars correspond to the 95% confidence intervals).

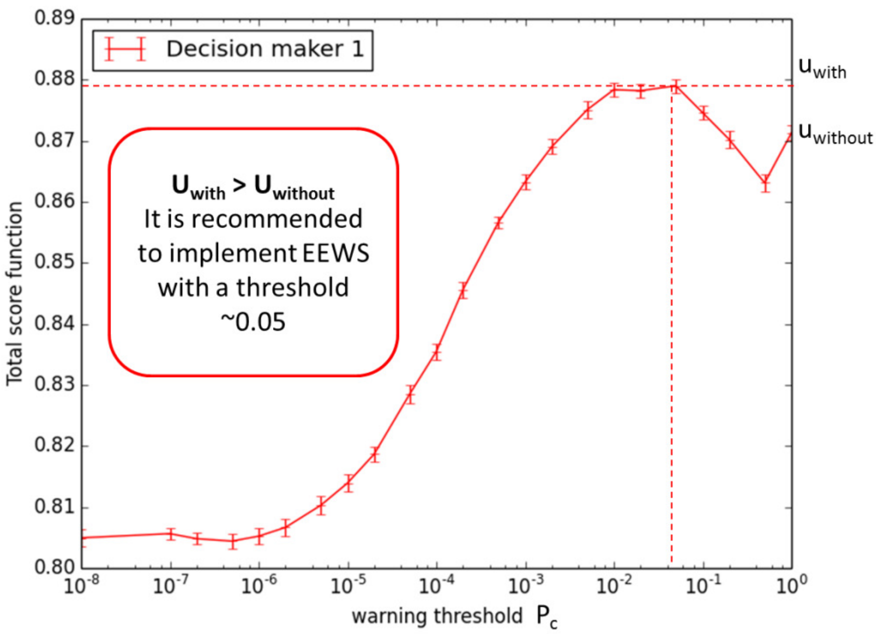

Figure 11 : Expected value of the global utility function depending on the warning threshold for DM n°1.

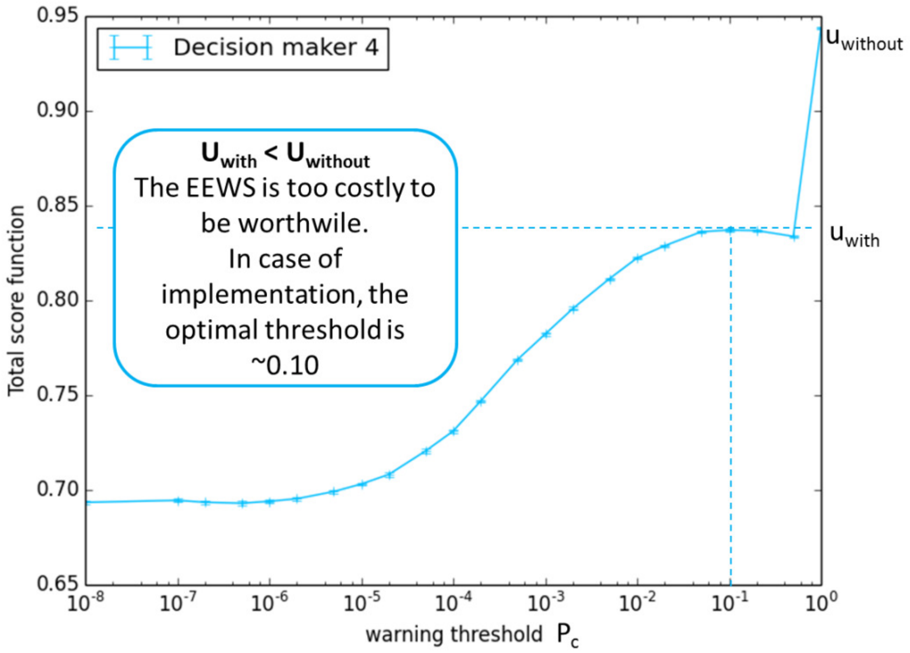

Figure 12 : Expected value of the global utility function depending on the warning threshold for DM n°4.

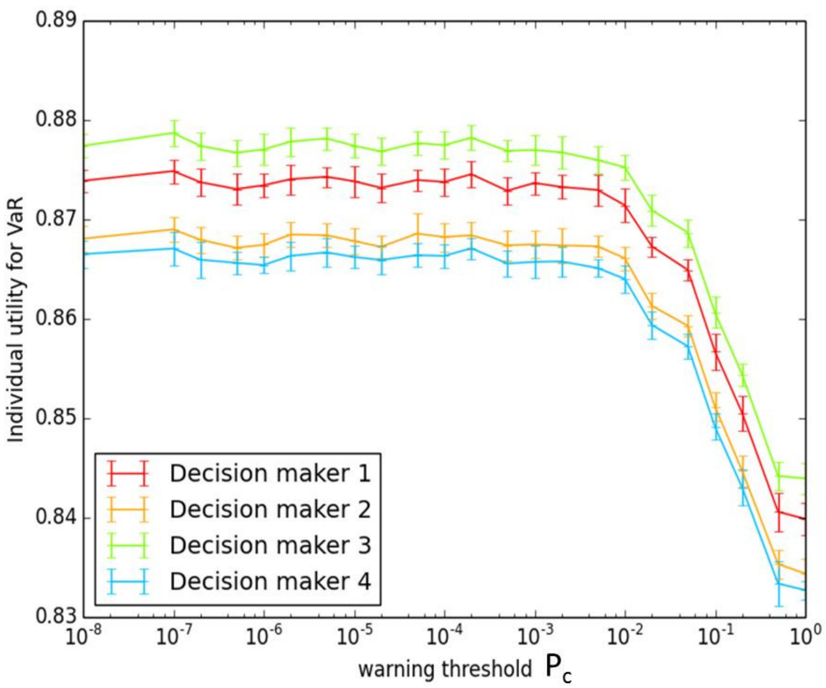

Figure 13 : Expected value of U_{VaR} depending on the warning threshold, with preferences from the four DMs (error bars correspond to the 95% confidence intervals).

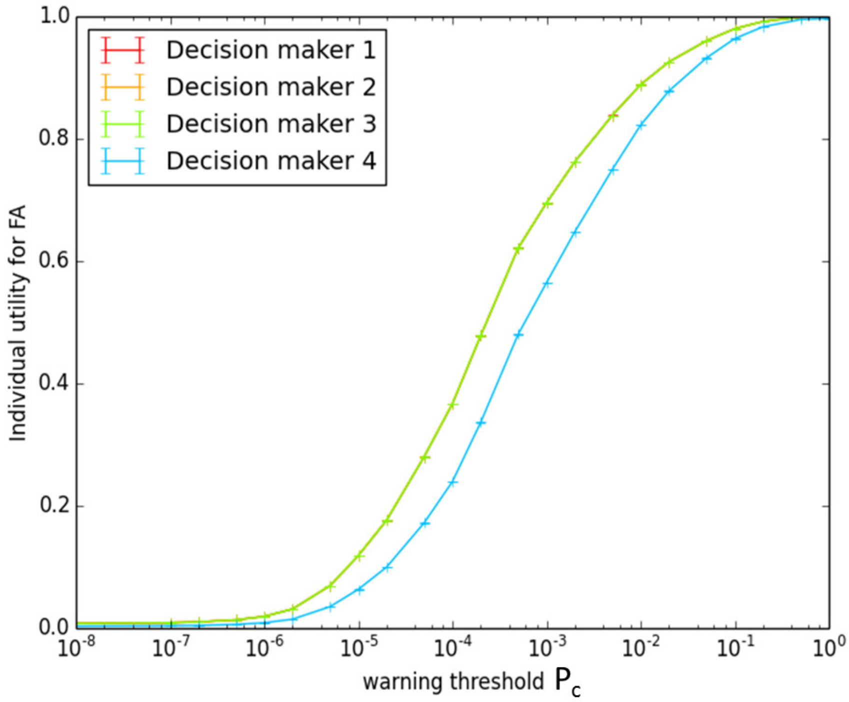

Figure 14 : Expected value of U_{FA} depending on the warning threshold, with preferences from the four DMs. The first three curves are identical (Error bars correspond to the 95% confidence intervals).

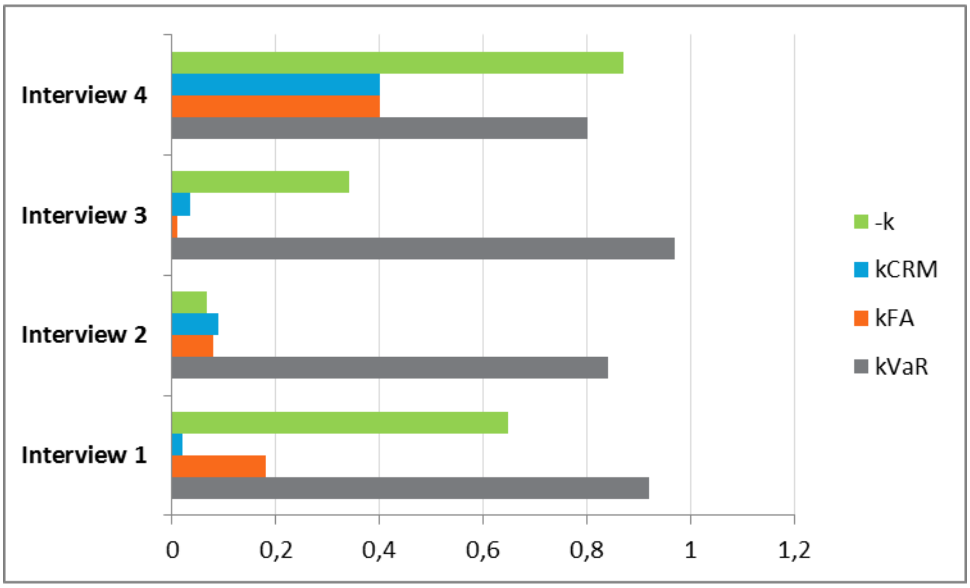

Figure 15 : Comparison of the constants of the global utility function from the four interviews