Decision criteria for Earthquake Early Warning applications

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SUMMARY:
The recent large earthquakes have emphasized the importance of earthquake loss mitigation and how earthquake early warning (EEW) systems can help. An EEW system detects an earthquake initiation based on a seismic sensor network and broadcasts a warning of the predicted location and magnitude shortly before an earthquake hits a site. The typical range of this lead time is around tens of seconds to a minute, which becomes a huge challenge for applications taking advantage of EEW. As a result, a robust automated decision process about whether to initiate a mitigation action is essential. Recent approaches propose taking an action upon exceedance of a fixed threshold for an intensity measure or damage or loss measure, but the determination of the threshold value remains as an open-ended question. In this study, a more robust decision criterion based on a new cost-benefit analysis procedure is proposed as part of an earthquake probability-based automated decision-making (ePAD) framework and an example is presented.

Keywords: Decision making, Earthquake Early Warning, Cost-benefit analysis

1. INTRODUCTION

Due to the large uncertainty about the stress and strength distributions within the tectonic plates on Earth, earthquakes are one of the most unpredictable natural hazards. Accurate prediction of when an earthquake will happen is still not possible, but the concept of earthquake early warning can be achieved because of the rapid development of computing power and network communication (Heaton 1985). However, the EEW information is highly uncertain and provides only a limited amount of warning time. The *lead time* before seismic waves arrive at a site may range from a few seconds to a minute or so, corresponding to the time at which the strong shaking arrives at a site t_{arr} and current time t, i.e. $T_{lead} = t_{arr} - t$. Human intervention for loss mitigation would likely use up too much of the short lead time, preventing the mitigation from being activated in a timely manner. Therefore, an automated decision-making framework is essential for implementing many engineering applications of EEW.

Recent proposed decision methods use exceedance of a threshold for a predicted ground shaking measure (Grasso, Beck and Manfredi 2007, Iervolino, Giorgio and Manfredi 2007), but a robust method for determining the threshold is needed. Using cost-benefit analyses, an earthquake probability-based automated decision-making (ePAD) framework is developed to handle this problem, and also other major challenges, such as performing multi-action decision-making and including lead time uncertainty into the decision-making. In this paper, because of space limitation, we focus on how the ePAD framework can be used to compare and interpret different decision methods.

2. BACKGROUND

2.1. Fundamental Concepts and Current Development of EEW

A major earthquake excites various kinds of waves, including P-waves, S-waves and surface waves. The P-wave is the fastest traveling wave with the least destructive power, while the S-wave and the surface waves are slower waves with much larger destructive power. EEW exploits two important speed differences to provide early warning before the destructive waves arrive a site: 1) The speed difference between the P-waves and S-waves; 2) The speed difference between seismic waves and electronic signals (Satriano et al. 2011). Once a seismic network detects P-wave information, the EEW system will perform fast prediction of the earthquake magnitude, hypocenter location and origin time. As the seismic waves propagate, the seismic network will receive more data and continuously update the EEW predictions. Since the electronic signals travel a lot faster than seismic waves, the warning time provided by EEW system depends heavily on the distance between a site and the hypocenter. General warning time is around a few seconds to a minute or so.

Japan has had a national EEW system for roughly 6 years. During the Tohoku earthquake in March 2011 (Hoshiba et al. 2011), EEW is proven to be effective for providing early warning. Other regions, such as Taiwan, Istanbul in Turkey, Mexico City and Bucharest in Romania, have more localized regional systems (Allen et al. 2009b). Currently, an EEW system called the California Integrated Seismic Network (CISN) ShakeAlert System is also under beta-testing in California, USA. As currently planned, ShakeAlert is a relatively unique system because it will combine the outputs of three early warning algorithms, each based on a different theory: τ_c-P_d on-site algorithm (Bose et al. 2009), Earthquake Alarms Systems (ElarmS) (Allen et al. 2009a), and Virtual Seismologist (V-S) (Cua and Heaton 2007) (see Fig. 2.1). All three systems receive data from the same CISN seismic network and run their own algorithm to produce probability distribution functions (PDF) of earthquake magnitude, location estimation and origin time. Their output will be integrated in a central decision module, which will produce a PDF for earthquake magnitude, location and origin time.

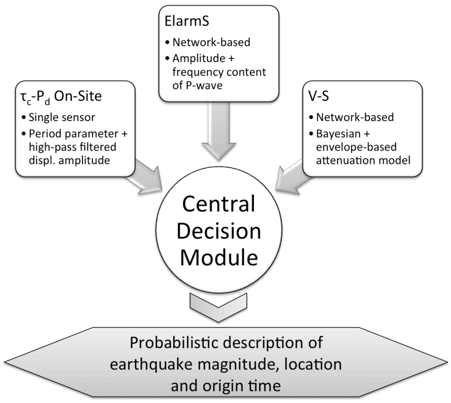

Figure 2.1. Planned structure of CISN ShakeAlert system.

2.2. Examples of Existing and Potential EEW Applications

Despite the rapid development of EEW systems around the world, its engineering applications lag behind. Some potential and existing applications are listed in Fig. 2.2. Due to the uncertainty of EEW predictions and short warning times, existing applications are only those with a low activation cost and a simple procedure. One of the most successful engineering applications of EEW is the Urgent Earthquake Detection and Alarm System (UrEDAS) of the Japan Railway Group (Nakamura, Sita and Sato 2011) for the high-speed Shinkansen trains. Other examples from recent literature include elevator control in a building (Kubo et al. 2011), semi-active structural control of a highway bridge (Maddaloni, Caterino and Occhiuzzi 2011) and seismic isolation system by air-bearings (Fujita et al. 2011). Recently, the concept of integrating EEW with structural health monitoring (SHM) in local damage detection (Rainieri, Fabbrocino and Cosenza 2011) or global loss assessment (Hilbring 2010) is mentioned by some research groups in Europe. Also, we have developed a synergistic framework between EEW and SHM to optimize the use of the information provided by both systems under a robust Bayesian probabilistic framework (Wu and Beck 2012).

	Simple Procedure	Complex Procedure
Low Action Cost	1. Warning broadcast 2. Elevator control(Kubo et al. 2011) 3. Open fire station garage doors	1. Emergency responder stand-by 2. Auto-saving for important data or running computer simulations 3. Air-bearings for small structures(Fujita et al. 2011)
High Action Cost	1. Stop traffic (traffic light/ highway entrance control) 2. Stop trains/metro (Japan Shinkansen – UrEDAS (Nakamura et al. 2007, 2011)) 3. Stop surgery in hospitals 4. Stop airplanes landing 5. Life-line control (water, gas, electricity, internet)	1. Active/semi-active structural control (base-isolator/active damper (Maddaloni et al. 2011)) 2. Theme parks shut down 3. Halt hazardous industrial processes 4. Terminate nuclear power plant activities

Figure 2.2. Categorization of potential and existing EEW applications.

2.3. Review of Recent Proposed Decision Framework for EEW

In many EEW applications, due to the limitation of short lead times, an automated decision-making system is needed to decide whether to trigger a mitigation action or not when the EEW information is received. As the information is uncertain, one could use a decision framework which activates an action when the probability of a ground shaking intensity measure (*IM)* exceeding some pre-set threshold im_0 is greater than some fixed value P_0. However, the determination of both threshold values im_0 and P_0 remains as an open-ended question.

In Grasso, Beck and Manfredi (2007), the authors introduced a tradeoff between the expected loss of false alarm and the expected loss of missed alarm to determine P_0. An action is activated when the expected loss of missed alarm is larger than the expected loss of false alarm. They show that this is indeed equivalent to the probability of *IM* exceeding a specified threshold im_0 being greater than a value P0 that depends on these expected losses. A more detailed explanation is included in Section 3.2.

Iervolino, Giorgio and Manfredi (2007) examined a decision framework to decide when to trigger an earthquake alarm inside a building. Instead of the threshold-based method, an expected-loss based method using the Performance-Based Earthquake Engineering (PBEE) approach (Porter 2003) is considered.

These methods make significant contribution to automating decisions for mitigation actions. However, there are still limitations for practical usage: 1) These decision frameworks generally apply to a single action decision, while some of the EEW applications involve decision making for multiple actions or a sequence of actions, such as transportation network problems, and so can not be applied directly; 2) The decision for most EEW applications is extremely time sensitive due to a short and uncertain lead time. We have developed a decision framework, called earthquake probability-based automated decision-making (ePAD), to handle both of these previously neglected concerns. In this paper, we focus on comparing the differences between these published decision methods using our ePAD framework.

3. DECISION FRAMEWORK

3.1. Basic Decision Framework for ePAD

EEW systems provide estimation of earthquake magnitude, hypocenter location and origin time based on early detection of the seismic waves. An optimal decision framework should be able to utilize all three pieces of information to provide a rational decision for taking mitigation actions. ePAD is a cost-benefit analysis-based decision framework that incorporates all the information with explicit treatment of its uncertainty. It is a very general framework that provides a platform for comparing many other decision methods.

A decision is usually made between available choices by balancing different tradeoffs from the consequences of the choices. Cost-benefit analyses are generally accepted as a rational way of quantifying different tradeoffs. Consequently, ePAD makes decisions solely based on a cost-benefit criterion and chooses an optimal action from a set of possible mitigation actions (including no action). For example, in the simplest binary decision situation, the alternatives are *To Take Action* or *Not To Take Action*. Taking a mitigation action often leads to some kind of interruption to the operation of the facility, business or society, while not taking an action induces a risk of larger earthquake losses. To compare possibly disparate consequences, they need to be converted into a single metric, called here a *Decision Variable* (DV), such as economic loss. Once we have a consistent metric for tradeoff comparisons, a rational decision-making procedure can be based on comparing the expected values of the *utility function* of DV, denoted as $U(DV)$, conditional on the EEW data. The decision criterion can be specified mathematically as follows.

Let: $\Omega_a = \{a_0, a_1, \ldots, a_n\}$, a set of alternative mitigation actions, where a_0 denotes taking no action
$E[X|Y,a]$ = expected value of X given Y for action a
$D(t)$ = data coming from EEW as a function of time t

then:

$$\textit{Take action} \quad \hat{a} = \operatorname{argmax}_{a \in \Omega_a} \{E[U(DV) \mid D(t), a]\} \tag{3.1}$$

Decisions based on expected utility can be categorized into risk-neutral, risk-averse and risk-seeking depending on the shape of the $U(DV)$ curve; for example, if DV is economic loss in dollars and a risk-neutral decision is to be made, then $U(DV) = -DV$ is appropriate. In Section 3.2, this concept is revisited to compare various decision frameworks.

Depending on the complexity of the mitigation actions in an EEW application, the calculation of expected-DV values may be difficult. As in Iervolino, Giorgio and Manfredi (2007), a PBEE methodology may be used to calculate the expected value, such as the PEER PBEE methodology shown in Fig. 3.1 and Eqn. 3.2, 3.3 and 3.4.

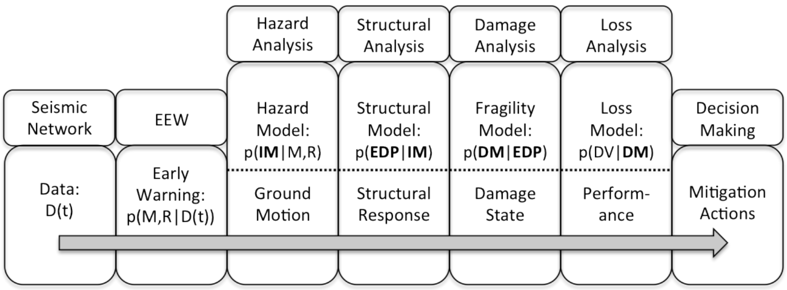

Figure 3.1. Information flow of PBEE-based EEW.

$$E[U(DV) \mid D(t), a] = \int E[U(DV) \mid \boldsymbol{IM}, T_{lead}, a]\, p(\boldsymbol{IM} \mid D(t))\, p(T_{lead} \mid D(t))\, d\boldsymbol{IM}\, dT_{lead} \tag{3.2}$$

where

$$p(\boldsymbol{IM} \mid D(t)) = \int p(\boldsymbol{IM} \mid M, \boldsymbol{R})\, p(M, \boldsymbol{R} \mid D(t))\, dM\, d\boldsymbol{R} \tag{3.3}$$

and

$$E[U(DV) \mid \boldsymbol{IM}, T_{lead}, a] = \int U(DV) p(DV \mid \boldsymbol{DM}, a) p(\boldsymbol{DM} \mid \boldsymbol{EDP}, a) p(\boldsymbol{EDP} \mid \boldsymbol{IM}, a) dDV d\boldsymbol{DM} d\boldsymbol{EDP} \quad (3.4)$$

Eqn. 3.4 is specific to the structural facility and it represents a pre-determined model for action a. Depending on how the models are setup, it may lead to different types of decision framework.

3.2. A Utility Point-of-view for Comparing Different Methods

For the convenience of comparison, let us consider a simplified case where $\Omega_a = \{a_0, a_1\}$, IM is a scalar such as the acceleration response spectral value S_a at some period, and the utility function $U(DV)$ is independent of T_{lead}. This is consistent with the decision frameworks mentioned in Section 2.3. For this simplified case, the previous decision criterion in Eqn. 3.1 becomes:

$$\textit{Take action iff} \quad E[U(DV) \mid D(t), a_1] > E[U(DV) \mid D(t), a_0] \quad (3.5)$$

This can be rewritten in the following form:

$$\textit{Take action iff} \quad \int \left(E[U(DV) \mid IM, a_1] - E[U(DV) \mid IM, a_0] \right) p(IM \mid D(t)) dIM > 0 \quad (3.6)$$

Now, define the ePAD *Decision Function*: $DF_{ePAD}(IM) = E[U(DV)|IM, a_1] - E[U(DV)|IM, a_0]$. Then, DF_{ePAD} is effectively a utility function for IM that is used for the decision-making. This is the Decision Function appropriate for the decision criterion of Iervolino, Giorgio and Manfredi (2007) where a PBEE methodology is used to evaluate the expected values.

For the threshold method mentioned in Section 2.3, one would determine fixed thresholds im_0 and P_0, perhaps based on engineering judgement, and the decision criterion would be:

$$\textit{Take action iff} \quad P(IM > im_0 \mid D(t)) > P_0 \quad (3.7)$$

Using the Heaviside step function $H(x)$, this can be rewritten in the following form:

$$\textit{Take action iff} \quad \int \left(H(IM - im_0) - P_0 \right) p(IM \mid D(t)) dIM > 0 \quad (3.8)$$

Thus, the ePAD Decision Function becomes for the threshold method: $DF_{TM}(IM) = H(IM - im_0) - P_0$.

For Grasso, Beck and Manfredi (2007), given a pre-specified threshold im_0 for IM that is set by the designers or operators of the facilities being protected, action is taken if and only if the expected cost of no action is greater than the expected cost of action. Two important expected costs are introduced: 1) An expected cost, C_{fa}, due to a false alarm is assumed if the mitigation action is taken but the IM at a site is less than im_0; 2) An expected cost, C_{save}, due to a missed alarm, and so a missed opportunity for mitigating the expected earthquake economic loss by C_{save}, is assumed if no action is taken but the IM at a site is larger than im_0. As a result, the decision criterion can be written as:

$$\textit{Take action iff} \quad C_{save} P(IM > im_0 \mid D(t)) > C_{fa} P(IM \leq im_0 \mid D(t)) \quad (3.9)$$

This can be rewritten in the following form:

$$\textit{Take action iff} \quad \int \left(H(IM - im_0) - \frac{C_{fa}}{C_{save} + C_{fa}} \right) p(IM \mid D(t)) dIM > 0 \quad (3.10)$$

If we take $P_0 = C_{fa}/(C_{save} + C_{fa})$ under this method, then its *Decision Function* is the same as $DF_{TM}(IM)$.

Another possible method is to take action if the occurrence of a specific damage state (DM_S) exceeds a certain threshold probability. For example, one may take a mitigation action when the probability of severe building damage exceeds P_{DM}. The decision criterion can be written as follow:

$$\textit{Take action iff} \quad P(DM_S \mid D(t)) > P_{DM} \tag{3.11}$$

This can be rewritten in the following form:

$$\textit{Take action iff} \quad \int \left(P(DM_S \mid IM) - P_{DM} \right) p(IM \mid D(t))\, dIM > 0 \tag{3.12}$$

Thus, the *Decision Function* for this case is: $DF_{DM}(IM) = P(DM_S|IM) - P_{DM}$.

Now, let us define *Decision Contour* as a contour that separates the region of a_0 (no action) and a_1 (take action) in an appropriate decision parameter space. For instance, $p(IM|D(t))$ is commonly modelled as a Gaussian or lognormal distribution in civil structure applications. One can define $p(IM|D(t))$ in a two-dimensional space based on the mean and variance of *IM*. Hence, the *Decision Contour* is a curve in this space that separates the region of a_0 and a_1.

Different types of *Decision Function* will result in different shapes of *Decision Contour*. Let μ_{IM} and σ^2_{IM} be the mean and variance of *IM* respectively, the decision contour can be found by either directly solving for the μ_{IM} and σ^2_{IM} roots of the decision criterion or first to create a fine mesh of μ_{IM} and σ^2_{IM}, then simulate and record the result of all decisions, and a boundary curve can be observed separating the region of a_0 and a_1. Fig. 3.2 shows a general shape of each decision function mentioned above. Analysis of decision contours obtained from different decision functions is performed in Section 4.2 based on an example.

In civil structure applications, $P(DM_S|IM)$ can be represented by a fragility curve, which is usually a type of sigmoid function, and DM_S is usually a vector of discrete damage states instead of a single damage state. Also, DF_{ePAD} can be viewed as a linear combination of sigmoid functions, which is also a sigmoid function, because $E[U(DV)|IM,a] = \Sigma_k\{E[U(DV)|DM_k,a]P(DM_k|IM,a)\}$, where $E[U(DV)|DM_k,a]$ is known once a loss model is defined for each DM_k. Therefore, one can determine P_{DM} by fitting DF_{ePAD} with DF_{DM} of any chosen DM_S. The regression problem can be solved by optimizing an objective function, for example, least-squares matching between the *Decision Contours* of DF_{ePAD} and DF_{DM}. An example of how to determine the effective P_{DM} in DF_{DM} and im_0 in DF_{TM} using DF_{ePAD} is covered in Section 4.1.

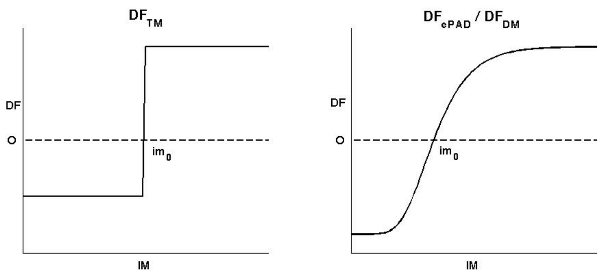

Figure 3.2. General shapes of decision functions.

3.3. Other Advantages of ePAD

In some EEW applications, more than one action is available. For example, in a complex bridge network, one may consider closing some of the bridges when EEW is received. Let n be the number of bridges, then there will be 2^n possible closure combinations to explore to maximize the expected utility function. ePAD is a very general decision framework that allows searching for an optimal choice among multiple actions, while this cannot be readily done by other published decision frameworks. Furthermore, since the lead time for the EEW system is both extremely short and uncertain, the time factor plays an important role in any decision-making. Due to the uncertain nature of EEW information, the decision for optimal mitigation actions can have dramatic change depending on the amount of time left for action. Some actions may have much less benefit if they are incomplete. Therefore, when the lead time is too short to complete an action, the cost-benefit analysis should not be the same as the case that there is sufficient time to complete an action. On the other hand, some EEW systems may provide continual updates of information. Then, if there is sufficient time to wait for new EEW information and complete the mitigation actions, one may want to delay making any decision so as to hope for more accurate EEW updates in the future. All these factors are included in the full ePAD framework, which, because of space limitation here, we will present at a later time.

4. EXAMPLE AND RESULTS

Let us take the PEER benchmark building studied in Haselton et al. (2007) and Goulet et al. (2007) as the target structure for our example. It is a hypothetical four-story reinforced concrete moment-frame building designed according to the 2003 International Building Code, located on deep sediment near the center of the Los Angeles basin, at 33.996◦N, 118.162◦W, south of downtown Los Angeles. Their study includes the details of structural models, fragility curves and annual loss assessment. In our example, let us consider a single action a_1: broadcasting an evacuation alarm. This action is chosen for testing the framework, but in real earthquakes, it is always encouraged to practice drop, cover and hold, instead of trying to exit from a building.

4.1. Threshold Determination with ePAD Framework

Determining a reasonable value for thresholds P_{DM} and im_0 in DF_{DM} and DF_{TM}, respectively, is a challenging problem. In the ePAD framework, this can be solved based on a cost-benefit analysis approach. After determining an appropriate loss model, im_0 and P_{DM} can be found by fitting the decision contour of DF_{DM} to the decision contour of DF_{ePAD}. Least-squares matching between the *Decision Contours* of DF_{ePAD} and DF_{DM} is chosen for convenience in this example.

In our example, the action tradeoff is between the expected life saving and business downtime cost due to triggering an evacuation alarm. Two damage states are considered: *Collapse* (DM_c) and *Partial Collapse* (DM_{pc}). *IM* is taken to be the spectral acceleration at the first mode period, $SA(T_1)$. The fragility curves for both damage states are shown in Fig. 4.1.

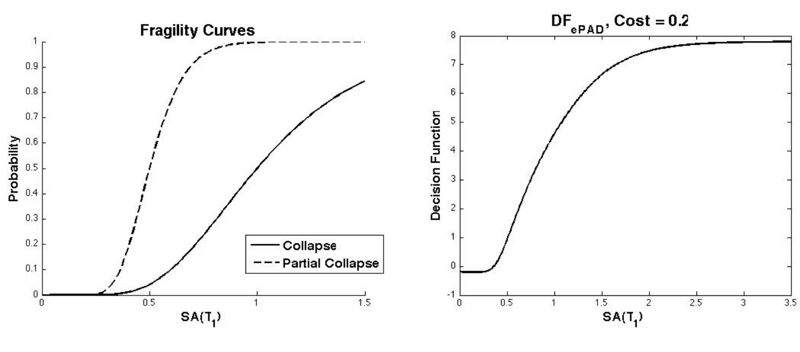

Figure 4.1. Structural model (left) and decision function (right) for the benchmark building.

In the PEER study, the expected life loss for collapse and partial collapse was taken as 20 and 2, respectively. Expected injury is converted into equivalent life loss and is included in the analysis. Let us assume a life saving factor of 0.4 and 0.8 for collapse and partial collapse respectively. Hence, given fragility curves for collapse and partial collapse, $P(DM_c|SA)$ and $P(DM_{pc}|SA)$, $E[U(DV)|SA,a_0]$ can be calculated as follow, assuming DV is the earthquake loss:

$$E[U(DV) \mid SA, a_0] = 0.4 \cdot 20 \cdot P(DM_c \mid SA) + 0.8 \cdot 2 \cdot P(DM_{pc} \mid SA) \tag{4.1}$$

Now, $E[U(DV)|SA,a_1]$ should be estimated by converting the business downtime into an equivalent life saving constant. Here, we assume a reasonably low value of 0.2. As a result, DF_{ePAD} can be found as shown in Fig. 4.1. Let us model $p(SA|D(t))$ as a lognormal distribution. Then, a decision contour can be found in the 2-D space of the mean and variance of SA. We can now determine P_{DM} by least-squares matching between the decision contours of DF_{ePAD} and DF_{DM}, where $P(DM|IM)$ in DF_{DM} is taken to be $P(DM_c|SA)$. Fig. 4.2 shows the resulting decision contours of both DF_{ePAD} and DF_{DM} after fitting.

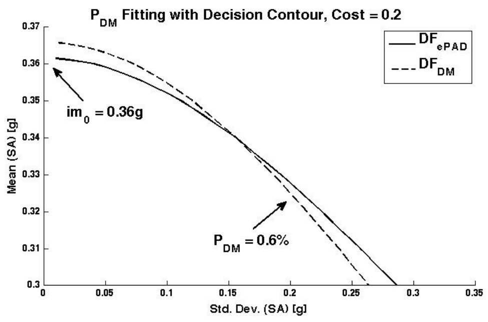

Figure 4.2. Decision contours used for determining im_0 and P_0. Region above a curve represents taking action, while region below a curve represents no action.

Using relatively low business downtime estimation, we obtained relatively conservative threshold values for both im_0 and P_{DM}. Since im_0 is the critical IM value when uncertainty is zero, it is found to be 0.36g from Fig. 4.2. For the damage-state-based method, the alarm is triggered when the probability of collapse exceeds 0.006. One can observe that the decision contour of DF_{DM} is steeper than the one of DF_{ePAD}, which leads to a more conservative decision, because as uncertainty increases, the alarm is always triggered at a lower mean value of SA if their vertical interceptions (i.e. im_0) are the same.

4.2. Influence of Decision Function on Decision Contour

In this section, we further investigate how various decision functions lead to different decision contours, thus, different decision behaviors. For consistency in the following analysis, we also use a lognormal distribution to model $p(SA|D(t))$, where $ln(\mu)$ and σ are the mean and standard deviation of $\ln(SA)$ respectively. We let sa_0 be the pre-set threshold for SA.

For the threshold method, we can obtain a closed form solution for the decision contour as follows:

$$P(SA > sa_0 \mid D(t)) = \frac{1}{2} - \frac{1}{2} erf\left[\frac{\ln(sa_0) - \ln(\mu)}{\sqrt{2}\sigma}\right] = P_0 \tag{4.2}$$

implies that:

$$\mu = (sa_0) e^{-\left(\sqrt{2} erf^{-1}[1-2P_0]\right)\sigma} \tag{4.3}$$

or

$$\ln(\mu) = \ln(sa_0) - \sqrt{2} erf^{-1}[1-2P_0]\sigma \tag{4.4}$$

Fig. 4.3 shows the corresponding decision contours for a fixed sa_0 and varying P_0. One can see that P_0 = 0.5 refers to a risk-neutral behavior, while P_0 less or greater than 0.5 refers to a risk-averse or risk-taking behavior, respectively.

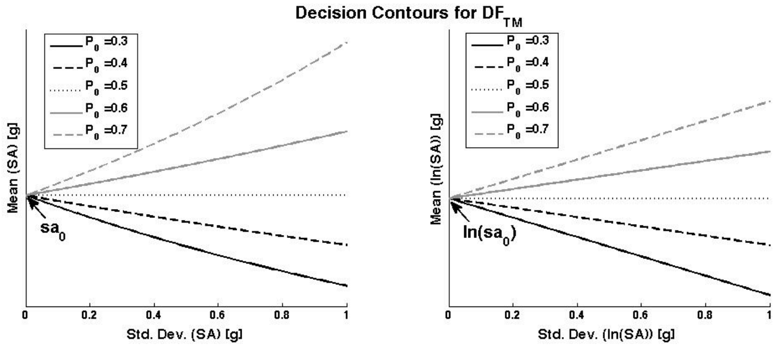

Figure 4.3. Decision curves for traditional threshold method. Region above a curve represents taking action, while region below a curve represents no action.

For the damage state-based method and ePAD, a similar analysis can be done numerically. Fig. 4.4 shows the corresponding decision contours for both methods with varying P_{DM} and $E[U(DV)|SA,a_0]$.

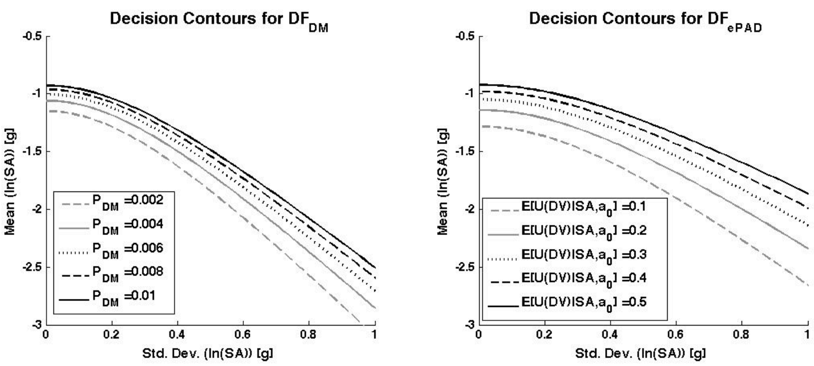

Figure 4.4. Decision curves for DF_{DM} (left) and DF_{ePAD} (right). Region above a curve represents taking action, while region below a curve represents no action.

Note that unlike the threshold method, varying the parameters in DF_{DM} and DF_{ePAD} does not change the shape of the decision contours, but rather shifts the critical *SA* value, because for these two methods, the shape of the contours is controlled by the fragility model of the target structure. Since both the collapse fragility curve and the chosen loss model put larger emphasis on the potential loss given by a high SA value, a risk-averse type of decision contour is obtained. With a different structural and loss model, the decision contour can be tuned more precisely to the structural owner's requirements, such as changing the curvature of the contour. This is not possible for the traditional threshold method, because the two thresholds can only shift or rotate the contour. In fact, when the full ePAD framework is used, other factors, such as the influence of lead time may significantly change the resulting decision contours, that allows a more flexible choice of risk preference behavior.

5. CONCLUSION

The benefits and feasibility of EEW is becoming more appreciated throughout the world. It is expected that an EEW system will be available to the public in California in the near future. In order to maximize the benefits of EEW, an automated decision-making framework is essential to tackle the very short lead times and high uncertainty. Recent proposed methods rely on some pre-set thresholds, but there is a lack of a systematic way of determining the thresholds. Our proposed framework, ePAD, is a more general decision framework that can also be used as a tool to compare existing methods. In this paper, the ePAD framework, which is a cost-benefit analysis-based approach, is briefly illustrated. A simple case that only involves binary decision-making (whether to take a mitigation action or not) is studied to compare the effect of using different methods from a utility point-of-view. The concepts of *decision function* and *decision contour* are introduced to visualize the differences. These concepts from the ePAD framework allow a better understanding of the decision behavior of various methods that have been proposed for automated EEW decision making.

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