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AN AUTOMATED DECISION-MAKING SYSTEM FRAMEWORK FOR EARTHQUAKE EARLY WARNING SYSTEM APPLICATIONS

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Abstract: Earthquakes are one of the most unpredictable natural hazards but recently short-lead-time Earthquake Early Warning Systems (EEWS) have become practical with a system operating in Japan and another planned for operation in California in the next year or two. A few seconds to a minute or so of early warning is achievable. For example, if appropriate, an early warning can be broadcast to enhance the effectiveness of evacuations, water and gas supplies can be temporarily cut off, and other more advanced engineering applications may also be developed. Due to the limited warning time and the uncertainty of the information from an EEWS, applications that require real-time human decision-making are not practical. This motivates recent research to develop a robust automated rapid decision-making procedure for mitigation actions. A rational procedure is to initiate a potential loss-reduction action if, based on the incoming information from an EEWS, the expected loss from taking no action is greater than the expected loss from taking the mitigation action. To estimate the expected loss of a predicted event, it is proposed to use the recently developed PEER performance-based earthquake engineering methodology.

1. INTRODUCTION

Due to the high uncertainty of 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. *Earthquake Early Warning Systems* (EEWS) have been operating in several different regions. Japan has a long history of earthquake monitoring: Urgent Earthquake Detection and Alarm System (UrEDAS) of the Japan Railway Group is one of the first applications of EEWS and now most regions in Japan are covered by a public warning broadcast network operated by the Japan Meteorological Agency (JMA) (Allen et al. 2009b, Doi 2000, Yamazaki and Meguro and Noda 1998). In Mexico, warnings are issued to the general public as well. In Taiwan, Istanbul and Bucharest, warnings are released to one or more users outside the research community (Allen et al. 2009b). Currently, an EEWS, called the California Integrated Seismic Network (CISN) ShakeAlert System, is also under testing in California, USA.

Early warning systems are usually based on P-wave detection that exploits the slower transmission velocity of S-waves, the main destructive wave, relative to electronic signals and P-waves. Comparing to other natural hazard early warning systems, the main challenge of EEWS is the extremely short *lead time*, defined as the time elapsing between the moment when the occurrence of a catastrophic shaking event at a given location is known to be reasonably certain to occur and the moment it actually occurs (Gasparini et al. 2007). Therefore, it is necessary to develop an *Automated Decision-making System* (ADS), which can make fast rational decisions based on the information from an EEWS. Here, we use expected economic loss as a basis for rational decision-making, and the *Pacific Earthquake Engineering Research Center* (PEER) *Performance-Based Earthquake Engineering* (PBEE) methodology (Porter 2003) is used for seismic loss estimation during the decision process. However, due to the complexity of the methodology, such a decision process suffers from long computation times. In order to obtain a fast ADS framework, the concept of *Action Function* and *Surrogate Model* are utilized in this paper. Combining all these ideas, a complete ADS framework is presented.

2. BACKGROUND

2.1 Brief Overview of EEWS in California, USA

The CISN ShakeAlert System, as currently planned, combines the outputs of three early warning systems each based on a different theory: τ_c-P_d on-site algorithm, Earthquake Alarms Systems (ElarmS), and Virtual Seismologist (V-S) (see Fig.1). The τ_c-P_d on-site algorithm is based on observations from a single sensor with two key parameters: period parameter τ_c and high-pass filtered displacement amplitude P_d. Vertical components of velocity and/or displacement data within the first three seconds window of P-waveforms is used to determine both parameters (Bose et al. 2009). On the other hand, ElarmS and V-S are regional network-based EEWS. ElarmS's earthquake location estimation is mainly based on a grid search to minimize arrival time residuals when there are more than 2 sensors triggered in the network. Its magnitude estimation relies on the amplitude and frequency content of the detected P-wave. Acceleration, velocity, displacement and predominant period (Allen and Kanamori 2003) are continuously determined from the vertical component of P-waves from all stations (Allen et al. 2009a). The V-S algorithm is based on a Bayesian method, which combines prior information with a likelihood function to narrow down the uncertainties. The V-S location estimation uses Voronoi Cells with a probabilistic approach. Its magnitude estimation relies on an attenuation model that is based on P-wave and S-wave envelopes (Cua and Heaton 2007). The likelihood function is formulated in terms of the attenuation model, while prior information, such as network topology, station health status, regional hazard maps, earthquake forecasts, etc., may be utilized to construct the prior probability density function (PDF). The PDF for the earthquake magnitude is then found by combining both likelihood function and prior PDF using Bayes' Theorem (Cua et al. 2009).

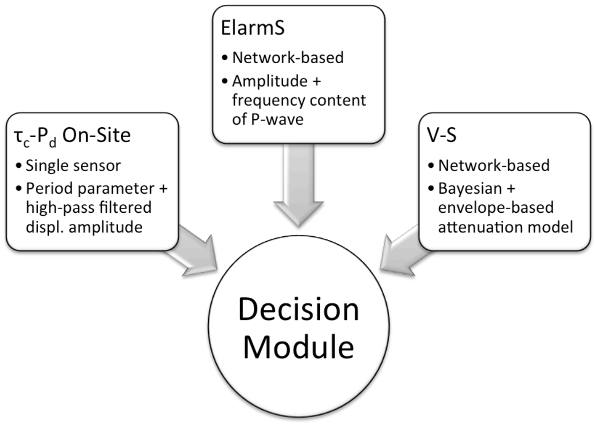

Figure 1 Structure of CISN Shake Alert System

All three systems receive data from the same CISN seismic network. Once a station is triggered within the network, each system will run its own algorithm to produce PDFs of earthquake magnitude and location estimation based on the received data signals. Then, all results will be integrated in a centralized module, called the Decision Module (Fig.1), which will produce a PDF for earthquake magnitude and location estimates based on the PDFs from all three systems.

2.2 Importance of ADS for Applications of EEWS

A few seconds to a minute of early warning can provide significant benefits to society. For example, through broadcasting an early warning of an earthquake, the efficiency of evacuation of at-risk structures or hazardous locations can be enhanced. Also, an automated action can be taken to mitigate the impending earthquake's impact on society, such as temporarily cutting off water and gas supplies. However, we believe that the true power of EEWS will only be achieved through more sophisticated engineering applications, which in many cases will involve mitigation actions that have significant resulting costs, including significant downtime losses caused by interference with normal operations. The decision of whether to activate such a mitigation action is a complicated tradeoff problem which, if time allowed, would best be done by human decision-making. Unfortunately, due to the limited warning time and the uncertainty in the predictions from EEWS, applications that involve human decision-making are not practical. Therefore, it is important to develop a decision-making system that can make rational decisions given uncertain predictions, as well as to make fast enough decisions in order to maximize available lead time for responding to the warning from the EEWS. This motivates the research presented here to develop a general framework of ADS. By using ADS, the utility of EEWS may be extended to cover a broader range of engineering applications. Hence, the impact of future large-scale earthquakes to society can be mitigated.

3. ADS FRAMEWORK

A decision is usually made between available choices by balancing different tradeoffs from the consequences of the choices. For EEWS applications, the automated system must choose whether to take mitigation actions or not based on a pre-determined criterion. In the simplest situation, the alternatives are **To Take Action** or **Not To Take Action**. Taking an 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 hazardous losses. To compare possibly disparate consequences, they need to be converted into a single metric, called here a *Decision Variable* (DV). Once we have a consistent metric for tradeoff comparisons, a rational decision-making procedure can be based on comparing the expected values of the DV, conditional on the EEWS data, for the two cases: action taken and action not taken. The decision criterion can be specified mathematically:

If smaller values of the chosen metric DV are preferred (i.e. it measures a negative/harmful event, such as economic loss or structural damage):

$$Take\ Action\ if\quad E_{\bar{A}}[DV|D(t)] \geq E_A[DV|D(t)] \quad (1)$$

If larger values of the chosen metric DV are preferred (i.e. it measures a positive/beneficial event, such as economic savings or structural damage avoidances):

$$Take\ Action\ if\quad E_{\bar{A}}[DV|D(t)] \leq E_A[DV|D(t)] \quad (2)$$

where:

$E_a[X|Y]$: $Expected\ value\ of\ X\ given\ Y\ for\ case\ "a"$
$D(t)$: $Data\ from\ EEWS\ as\ a\ function\ of\ time\ (t)$
a: $\bar{A}\ or\ A$; $\bar{A}$: $Action\ not\ taken$; A: $Action\ taken$

3.1 Calculation of the Expected Values

Depending on the complexity of the mitigation actions in an EEWS application, the calculation of expected DV values may be difficult. In order to illustrate the complexity of the problem, a commonly used DV, economic loss, is chosen. Economic loss is a very suitable metric in many cases because it is able to quantify different types of losses. It is also the DV in the PEER PBEE methodology, as shown in Fig.2.

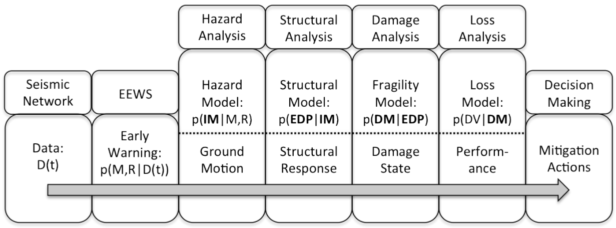

Figure 2 Information flow of PBEE-based EEWS (Grasso, Beck and Manfredi 2007)

In this figure, M and R are the magnitude and site-to-event distance of the incipient earthquake; **IM** is the ground shaking intensity measure; **EDP** is a vector of engineering demand parameters, and **DM** is a damage state measure for all the vulnerable components in the structure. Typical probability models for each analysis stage can be found, for example, in Goulet et al. (2007).

Using the PBEE methodology, the expected economic loss (denoted as DV in the following) can be calculated with the integral form as shown below (Goulet et al. 2007):

$$E_a[DV|D(t)] = \int DV p_a(DV|\boldsymbol{DM})\, p_a(\boldsymbol{DM}|\boldsymbol{EDP}) \ldots p_a(\boldsymbol{EDP}|\boldsymbol{IM}) p(\boldsymbol{IM}|M,R) p\big(M,R\big|D(t)\big) \ldots dDV d\boldsymbol{DM} d\boldsymbol{EDP} d\boldsymbol{IM} dM dR \tag{3}$$

Here, $p_a(x|y)$ denotes the PDF of x given y for case "a". Once all the PDFs are obtained from the models shown in Fig.2, the expected loss for both cases $\bar{A}$ and A are found. Then, a decision can be made based on (1) or (2).

Even though there is an explicit expression for calculating $E_a[DV|D(t)]$, there remains an important challenge for practical usage. Since it is not possible to analytically evaluate the integral for most practical applications, a numerical integration scheme that may require heavy computing power is necessary. As a result, the real-time decision-making process may not be fast enough for EEWS purpose. To solve this problem, the concepts of *Action Function* (AF) and *Surrogate Model* are introduced.

3.2 Action Function and Surrogate Model

In order to shorten the computational time for real-time decision-making, most parts of the expected loss calculation may be pre-calculated and stored in a computationally efficient form. This can be done by introducing the Action Function and a surrogate model. Let us first re-write (3) in a more compact form:

$$E_a[DV|D(t)] = \int E_a[DV|M,R]\, p(M,R|D(t)) dM dR$$

where

$$E_a[DV|M,R] = \int DV p_a(DV|\boldsymbol{DM})\, p_a(\boldsymbol{DM}|\boldsymbol{EDP}) \ldots p_a(\boldsymbol{EDP}|\boldsymbol{IM}) p(\boldsymbol{IM}|M,R) dDV d\boldsymbol{DM} d\boldsymbol{EDP} d\boldsymbol{IM}$$

is to be pre-computed. Define the Action Function (AF) by:

$$AF = E_{\bar{A}}[DV|M,R] - E_A[DV|M,R] \tag{4}$$

then from (1) and (2), the new form of the decision criterion becomes:

If smaller values of the chosen metric DV are preferred:

$$Take\ Action\ if\ and\ only\ if\ \ E[AF|D(t)] \geq 0 \tag{5}$$

If larger values of the chosen metric DV are preferred:

$$Take\ Action\ if\ and\ only\ if\ \ E[AF|D(t)] \leq 0 \tag{6}$$

where $E[AF|D(t)] = \int AF(M,R) p\big(M,R\big|D(t)\big) dM dR$

Note that AF in (4) can be pre-determined from the four probability models shown in Fig.2 because it is not related to real-time information from the EEWS. Therefore, all of the integrals giving AF can be pre-calculated so that AF(M,R) can be approximated by a surrogate model, thereby increasing the efficiency of calculating E[AF|D(t)]. It is expected that the EEWS in California will quantify the uncertainty in the predicted magnitude and location estimates by a Gaussian PDF p(M,R|D(t)), so we have chosen to use Gaussian radial kernel functions as a basis for a surrogate model for AF. Since both AF(M,R) and p(M,R|D(t)) have a Gaussian form, their product also has a Gaussian form and thus its integral can be written in an analytical form. The surrogate model regression scheme is chosen to be the relevance vector machine (RVM) because of its ability to provide a sparse and accurate regression model (Tipping 2001 and 2004, Tipping and Faul 2003, Bishop 2006). As a result, an efficient analytical form for E[AF|D(t)] can be obtained that significantly speeds up the real-time decision-making process.

3.3 ADS Framework Summary

Let us consider a simple EEWS application that contains only one mitigation action on a target structure/system. First, based on the PEER PBEE methodology, the Action Function is pre-calculated and approximated by the RVM using a Gaussian radial kernel basis. Next, as the EEWS starts to feed in earthquake estimates to ADS, E[AF|D(t)] is rapidly calculated as described above. An automated decision is then made based on (5) or (6) depending on the chosen DV, as well as the action time constraint:

Take back-up action or no action when $t_{left} < 0$

where $t_{left} = t_{EEWS} - t_{ADS} - t_{Act}$

t_{EEWS} = *remaining lead time from EEWS*

t_{ADS} = *average decision-making time delay*

t_{Act} = *time required to complete action*

The above time constraint checks if the remaining time is enough for completing the target mitigation action. If not, then either no action is taken or, if there exists one, the back-up action is taken which is not as effective as the principal mitigation action but that can be implemented in sufficient time. Fig.3 shows a summary of the structure of the ADS framework. For more complicated applications, such as multiple mitigation actions, this framework can be extended.

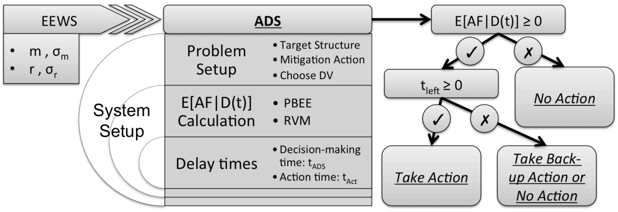

Figure 3 Structure of the ADS framework: m and r are the means of M and R; σ_m and σ_r are the standard deviations of M and R

4. CONCLUSION AND FUTURE WORK

The benefits and feasibility of EEWS is getting better appreciated throughout the world. It is expected that there will be one operating in California in a year or two. In order to maximize the benefits of EEWS, a fast ADS is essential to tackle the very short lead times. However, the whole process of rational decision-making requires a complicated model analysis and long computational times in general. Therefore, the only way to make it practical is to break up the computations so that many can be done prior to implementing ADS at a structure or facility. From the moment that EEWS releases warning information, the three main steps to achieve are performing the ground motion prediction at a chosen site, the response prediction for the target structure/system, and the loss/damage prediction. Since all three steps do not involve information from the EEWS, these can be done ahead of time and then approximated with a robust Bayesian surrogate model using the RVM. Combining the concepts of Action Function and the surrogate model, we can develop a fast ADS framework. The next step in our research is to investigate the framework for various case studies using past-earthquake data. We are currently doing so, but there remain some key challenges to apply the ADS framework. One of them is that it is difficult to quantify the benefit of a mitigation action. Over-estimating the benefit will increase the probability of taking a mitigation action when it should not have been done, while under-estimating will increase the probability of not acting when it is appropriate to do so. More research will be done on these kind of practical issues.

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