An Engineering Application of Earthquake Early Warning: ePAD-Based Decision Framework for Elevator Control

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Abstract: In a medium-to-large earthquake, there are often reports of people being trapped or injured in elevators. This study investigates using an earthquake early warning (EEW) system, which provides seconds to tens of seconds warning before seismic waves arrive at a site, to help people escape from the elevators before a strong shaking arrives. However, such an application remains as a major engineering challenge due to the uncertainty of the EEW information and the short lead time available. A recent study presented an earthquake probability-based automated decision-making (ePAD) framework to address these issues. This paper focuses on studying the influence of two commonly ignored factors, uncertainty of warning and lead time, on the decision of stopping the elevators and opening the doors when an EEW message is received. Application of the ePAD framework requires using the performance-based earthquake engineering methodology for elevator damage prediction, making decision based on a cost-benefit model and reducing computational time with a surrogate model. The authors’ results show that ePAD can provide rational decisions for elevator control based on EEW information under different amounts of lead time and uncertainty level of the warning. DOI: 10.1061/(ASCE)ST.1943-541X.0001356. © 2015 American Society of Civil Engineers.

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Introduction

Elevators in earthquake zones are often equipped with seismic sensors that can trigger an emergency shutdown to avoid falling or severe damage. However, specialists are required to check the integrity of the elevator and restart the elevator system after an emergency shutdown. Hence, after a large earthquake occurs, there might be significant loss caused by people being trapped in the elevators. One example is an M6.3 earthquake that happened on October 31, 2013, in Hualien, Taiwan, where there were reports of people trapped in the lifts (Yahoo News 2013). Earthquake early warning (EEW) systems, which provide a few seconds to a minute of warning lead time, open a new solution to prevent such tragedies—stop the elevator at the closest floor and open the doors before the arrival of the destructive seismic waves. Due to the uncertainty of EEW information, false alarms may occur, which would lead to unnecessary disruption to the elevator service that would trouble the passengers. Current practice is often to trigger a mitigation action when the expected intensity measure (IM) based on EEW information exceeds a preset threshold. A common approach for IM estimation is to use a ground motion prediction equation (GMPE) based on the estimated earthquake magnitude and hypocenter location (Boore and Atkinson 2008; Campbell and Bozorgnia 2008), although recently a new approach has appeared that directly estimates IM in a large region based on local IM data from seismic network stations (Hoshiba 2013). However, the shaking experienced in a tall building will be significantly different from that on the ground and it will also differ from one building to another, or even from one floor to another. During the April 7, 2011, M9.0 Tohoku earthquake in Japan, for example, roof accelerations on some tall buildings in the Tokyo metropolitan area were amplified by a factor of around 3.5 compared to the ground motions (Kasai et al. 2012).

This paper addresses this dynamic response amplification and provides a robust decision-making framework for elevator control based on uncertain EEW information from a simple structural model and a decision model. It is always a challenge to make rational decisions based on uncertain EEW information and structural models, and this is a major concern for any automated decision-making system. The authors use the recently published probability-based decision framework, ePAD (Wu et al. 2013), which was developed for this particular reason. This framework, which can be flexibly implemented for specific applications, allows users to easily pick their desired decision behavior (i.e., to control how uncertainty influences the decision). It also includes the contribution of warning lead time, which is a sensitive factor for EEW applications, to the decisions of whether to trigger the mitigation action or not. In order to ensure a fast and robust decision with ePAD, the authors use a trained surrogate model based on the relevance vector machine (RVM) from machine learning to emulate the complex cost-benefit model that includes the value of information (VoI). As an illustrative example, the authors
presented an application of ePAD to elevator control for a building in downtown Los Angeles and with an earthquake on the San Andreas Fault.

Background

Current EEW and Japan’s Elevator Control Strategy

EEW systems exploit the elapsed time due to the speed difference between seismic network signals and seismic wave speeds (P-wave, S-wave, and surface waves) to estimate and broadcast relevant earthquake information, such as the earthquake magnitude, hypocenter location, origin time, and local intensity measure (Hilbring et al. 2014), before the arrival of damaging waves. Typical warning time ranges from a few seconds to a minute or so, depending on various factors, such as seismic network density, geological structure of the region, and the site-to-hypocenter distance. Recently, an EEW system called the California integrated seismic network (CISN) ShakeAlert, has been developed in California. The system combines the outputs of three distinct early warning algorithms: $\tau_c - P_d$ on-site algorithm (Böse et al. 2009a, b), earthquake alarm systems (ElarmS) (Allen et al. 2009a), and virtual seismologist (V-S) (Cua and Heaton 2007). Fig. 1 demonstrates a sample user interface of the CISN ShakeAlert system. Detailed information can be found in Böse et al. (2014). In addition, a smartphone version of such a system is currently under development (Faulkner et al. 2011).

Japan’s EEW system, hosted by the Japan meteorological agent (JMA), has been broadcasting warnings since 2007 (Allen et al. 2009b). The warning can be received through cellphones, televisions, and the Internet. Particularly for applications to tall buildings, Kubo et al. (2011) investigated a method that combines an EEW system and a real-time strong motion monitoring system for a high-rise building in Tokyo, Japan. Their study also includes an elevator control system based on EEW. In their approach, elevators are moved to the closest floor and the doors are opened if the expected peak floor acceleration exceeds a preset threshold based on a Japanese standard. The expected peak floor acceleration is calculated based on the EEW information, a ground motion prediction equation, and a lumped-mass building model. In contrast, Cheng et al. (2014) conducted a study on elevator control that used a performance-based earthquake engineering framework and receiver operating characteristic (ROC) analysis. Their study presents a probability-based approach that utilizes data from the California Strong Motion Instrumentation Program database. A threshold to stop the elevators is chosen based on a trade-off between the empirical false alarm and missed alarm rate. In this paper, the authors investigate the influence of the uncertainties in the EEW information and warning lead time on decision making, which were not included in the previous studies.

ePAD Framework

The ePAD framework (Wu et al. 2013) utilizes the EEW information to robustly and rapidly choose an optimal action from a set of possible mitigation actions $\Omega = \{a_0, a_1, \ldots, a_n\}$, where $a_i$ denotes initiating a certain action for $i = 1, \ldots, n$, and $a_0$ denotes not to initiate any action. It makes decisions based on fundamental decision theory (Raiffa and Schlaifer 1961; Von Neumann and Morgenstern 1944), and it is designed to include the contributions of lead time and uncertainties from the selected models and EEW information in the automated decision making. ePAD provides a flexible platform for application-specific models in the decision-making process, and allows users to select structural and decision models that match their desired decision behavior.

ePAD makes decisions based on a cost-benefit approach. Applying a performance-based earthquake early warning (PBEEW)
Methodology (Grasso 2005; Iervolino et al. 2007), which is a combination of performance-based earthquake engineering (PBEE) and EEW, ePAD separates the EEW information from all the precalculable user-specific models (e.g., decision model, structural model, and/or GMPE), and lumps the latter into a single function called the decision function (DF). This leads to a simpler representation during calculation, an easier way of performing analyses, as well as allowing the possibility of replacing the precalculable function with a surrogate model for fast computing. The lead time contribution is embedded in the framework in two ways: an incomplete action model and a value of information model. The former considers the case where the benefit and cost of a mitigation action may change if it is not completed before the arrival of the damaging seismic waves; the latter considers the case where decision may be delayed if there is to be future updates of EEW information and the predicted lead time is more than enough to complete a mitigation action.

**Methodology**

**Basic Model (No Lead Time Contribution)**

For the elevator control application, examples of possible mitigation actions include immediate stop, stop at the closest floor, move to the ground floor, etc. For this study, a single action is considered—stop the elevator at the closest floor and open the door. For the basic model (decision making without the influence of lead time), let the action set \( \Omega = \{A_0, A_1\} \), where \( A_0 = \) no action and \( A_1 = \) take action. A decision is made based on the trade-off between the cost (induced economic cost after taking the action) and the benefit (reduced economic loss after taking the action), \( L_C \) and \( L_B \), respectively, given the seismic data \( D(t) \) at time \( t \). Following the ePAD framework, the authors use the decision function:

\[
\text{Take optimal action } A = \text{argmax}_A \text{DF}(D(t), A)
\]

\[
\text{where } E[\text{DF}(D(t), A)] = \int \text{DF}(IM, A)p(IM|D(t))dIM
\]

\[
\text{and } \text{DF}(IM, A) = E[L_B|IM, A] - E[L_C|IM, A]
\]

When no action is taken, there is no benefit and cost corresponding to the action, thus, the expected value of \( L_B \) and \( L_C \) given \( IM \) and \( A_0 \), \( E[L_B|IM, A_0] \) and \( E[L_C|IM, A_0] \), are both zero. Hence, \( E[\text{DF}(D(t), A_0)] = 0 \). On the other hand, \( E[L_B|IM, A_1] \) and \( E[L_C|IM, A_1] \) are calculated based on a loss model and a structural model. Let the cost of action be time delayed and service interruption from stopping the elevator, which occurs each time the action is taken. Hence, \( E[L_C|IM, A_1] = r_{c1}l_{c1} + r_{c2}l_{c2} \), a constant with respect to \( IM \), where \( l_{c1} \) and \( l_{c2} \) represent the expected amount of time delay and service interruption, respectively, affecting the passengers, and \( r_{c1} \) and \( r_{c2} \) represent the corresponding factors to transfer the loss terms, \( l_{c1} \) and \( l_{c2} \), to economic loss. Also, let the benefit of action be preventing injury or death for occupants trapped in the elevator after an earthquake. Hence, \( E[L_B|IM, A_1] = r_{b}l_{b}P(DM|IM, A_1) \), where \( P(DM|IM, A_1) \) represents the fragility function of damage state \( DM \) and is described in detail in the next section. Here, \( DM \) represents the state of elevator in danger (defined more specifically in the section of closed form solution for basic model), \( l_{b} \) represents the number of injured individuals, and \( r_{b} \) represents a factor to transfer injury to economic loss. The choice of \( r_{c1}, r_{c2} \), and \( r_{b} \) is directly related to the decision behavior, which will be discussed in detail later in the analyses and discussion section.

**Incomplete Action Model**

When lead time is too short to complete the action, an incomplete action model is considered by adding a discounting factor to both \( L_B \) and \( L_C \). These factors, as a function of warning lead time \( T_{lead} \), model potential change of benefit and cost of the action due to lack of time. Let \( \Omega_l = \{a_0, a_1\} \) be the new set of actions, where \( a_0 = \) no action at current time step and \( a_1 = \) take action at current time step. From ePAD

\[
\text{Take optimal action } a = \text{argmax}_{a\in[0,1]} \text{DF}(D(t), a_1)
\]

\[
\text{where } E[\text{DF}(D(t), a_1)] = \int \text{DF}(IM, T_{lead}; a_1)p(IM|D(t))p[T_{lead}|D(t)]dIMdT_{lead}
\]

**Structural Model**

A structural model is needed to calculate the fragility function \( P(DM|IM, A_1) \). This study adopts a generic structural model developed by (Miranda and Taghavi-Ardakan 2005) to readily predict peak floor accelerations (PFA), one of the controlling variables for the decision on elevator control, from peak ground acceleration (PGA), the chosen \( IM \) in this study. The chosen model categorizes buildings by four parameters: fundamental period \( T_1 \), modal damping ratio \( \zeta \), lateral stiffness ratio \( \alpha_0 \), and lateral stiffness reduction ratio \( \delta \). The dimensionless parameter \( \alpha_0 \) describes the participation of shear and flexural deformations in the model, which affects the lateral deflected shape of the building. The other dimensionless parameter \( \delta \) describes the variation of lateral stiffness along the building height. Taghavi-Ardakan (2006) concluded that lateral stiffness reduction has negligible effect on the prediction of floor responses over a practical range of stiffness reduction, so \( \delta = 1 \), i.e., uniform stiffness along the height is adopted in this study. A typical value of modal damping ratio \( \zeta = 5\% \) is selected. This study considers three values of \( \alpha_0 \) suggested by Miranda and Reyes (2002): \( \alpha_0 = 12.5 \) is used for moment resisting frame buildings; \( \alpha_0 = 3.125 \) is used for dual system (e.g., resisting frame and shear wall) buildings; and \( \alpha_0 = 1 \) is used for shear wall buildings. The fundamental period \( T_1 \) is predetermined for each building. Figs. 2 and 3 show the mean \( \mu_{ST} \) and standard deviation \( \sigma_{ST} \) of ln(PFA/PGA) along the building height. For a set of selected values of the four building parameters in the model, which determines the values of \( \mu_{ST} \) and \( \sigma_{ST} \), the probability of PGA given PFA is expressed as

\[
p(PFA|PGA) = \phi \left( \frac{\ln(PFA) - \ln(PGA) - \mu_{ST}}{\sigma_{ST}} \right)
\]

This continuum model combines a flexural cantilever beam and a shear cantilever beam that inherits some limitations, such as linear elastic behavior and classical damping. Also, tall buildings are more sensitive to long-period acceleration, while short buildings are more sensitive to high-frequency acceleration. Therefore, the estimation of PFA based on PGA by this model may not be the best choice, because PGA is controlled by high-frequency components of the ground motion. This model is selected because a probability distribution for PGA given PFA is available (Taghavi-Ardakan 2006) and the log-normally distributed PFA results in closed form solutions that provide insights into how the uncertainty of different model parameters influences the decision behavior.
and \( DF(IM, T_{lead}, a_i) = \beta_i(T_{lead})E[L_B|IM, A_i] \)
\[ - \gamma_i(T_{lead})E[L_C|IM, A_i] \] (7)

Similar to the basic model case, \( DF(IM, T_{lead}, a_0) = 0 \), \( E[L_B|IM, A_1] \), and \( E[L_C|IM, A_1] \) are the same as in the basic model, and the discounting factors \( \beta \) and \( \gamma \) as a function of \( T_{lead} \) are chosen as follows:

Let \( T_a \) be the amount of time required to finish the action. When \( T_{lead} < T_a \), the elevator cannot appropriately stop at the closest floor and open the door for people to evacuate. Thus, \( \beta_1 \) is assumed to be a step function with value of zero when \( T_{lead} < T_a \), and with value of 1 otherwise. This represents an all-or-nothing benefit model. For the time delay and service interruption cost, \( \gamma_1 \) is assumed to be a simple linear function with value between \( r_0 \) and 1 when \( T_{lead} < T_a \), where \( r_0 \) represents the ratio of fixed cost (independent of \( T_{lead} \)) over the total cost. In this study, the service interruption cost \( r_{C2}l_{C2} \) is taken as a fixed cost, thus, \( r_0 = r_{C2}l_{C2}/(r_{C1}l_{C1} + r_{C2}l_{C2}) \). Fig. 4 shows the value of \( \beta_1 \) and \( \gamma_1 \) as a function of \( T_{lead} \). [\( \beta_0 \) and \( \gamma_0 \) are not needed because \( DF(IM, T_{lead}, a_0) = 0 \)].

**Value of Information Model**

If an EEW system continually provides early warning information, one may want to delay a decision of initiating a mitigation action when the expected warning lead time is sufficiently long and the

**Fig. 2.** Mean of floor acceleration demand: \( z \) is the height of the level considered; \( H \) is the total height of a building; and \( \alpha_0 \) is the lateral stiffness ratio (data from Taghavi-Ardakan 2006)

**Fig. 3.** Standard deviation of floor acceleration demand: \( z \) is the height of the level considered; \( H \) is the total height of a building; and \( \alpha_0 \) is lateral stiffness ratio (data from Taghavi-Ardakan 2006)

**Fig. 4.** \( \beta_1 \) and \( \gamma_1 \) as a function of \( T_{lead} \).
current EEW information is very uncertain. This is a trade-off between the potential benefit of having less uncertain EEW information and the potential cost of not being able to complete the action. ePAD models this extra cost-benefit factor using a value of information (VoI) model (Howard 1966), which estimates the expected marginal benefit of delaying the decision, or in other words, not to take any action now (action \( a_0 \)). Hence, \( E[DF|D(t),A_0] \equiv \text{VoI} \) instead of zero. From ePAD (Wu et al. 2013)

\[
\text{VoI} = \int \int \Delta t, a_0, |p[IM|D(t)]|p[T_{lead}|D(t)]dIMdT_{lead} \tag{8}
\]

Here, \( \Delta t \) is the expected time interval for the next EEW update. With the max function involved, VoI often does not have a closed form solution and so a numerical approximation must be made. This approximation can be prelearned by a surrogate model so that it can be rapidly computed as the EEW information arrives. In this study, the RVM from machine learning (Tipping 2001) is chosen to construct a surrogate model for VoI because of its ability to create a sparse model using a Bayesian approach. Results are shown in the section of numerical solution for value of information model using surrogate model.

**Analyses and Discussion**

### Closed Form Solution for Basic Model

In the basic model, the only incoming EEW information is \( p[IM|D(t)] \), which is typically modeled as a Gaussian distribution with \( \mu_{IM} \) and \( \sigma_{IM} \) as the mean and standard deviation of \( IM \) for \( IM = \ln \text{PGA} \). This study investigates the influence of each model parameter on decision behavior using the decision contour method introduced in EPAD—a map of action and no-action regions partitioning the 2D parameter space of \( \mu_{IM} \) and \( \sigma_{IM} \). The resulting critical contour that separates the two regions, called the decision contour, is used to interpret different decision behaviors.

According to the State of California (Cal/OSHA) regulation standards, an earthquake sensing device must be installed in every elevator to trigger an emergency shutdown if the detected acceleration is more than 0.5 g (Cal/OSHA 2012). In contrast, Japanese elevator regulation requires elevators to stop operation at a much lower threshold—0.08 to 0.15 g of acceleration depending on building properties and elevator location (Kubo et al. 2011). Let the natural log of the threshold on PFA be \( \ln pfa_0 \); examples in this study use the Cal/OSHA standard, \( \ln pfa_0 = \ln(0.5) \). Given the chosen structural model [a Gaussian model on \( \ln(PFA/PGA) \) depending on structural properties [Eq. (4)]] the fragility functions \( P(DM|IM,A_1) \) and \( P(DM|D(t),A_1) \) are described as follows:

\[
\text{Let } p(IM|D(t)) = \Phi \left( \frac{\ln \text{PGA} - \mu_{IM}}{\sigma_{IM}} \right) \tag{9}
\]

and

\[
P(DM|IM,A_1) = P(\ln \text{PFA} > \ln pfa_0 | \ln \text{PGA}) \tag{10}
\]

\[
\text{Let } p(IM|D(t),A_1) = \int P(DM|IM,A_1)p(IM|D(t)|dIM
\]

\[
= \Phi \left( \frac{\mu_{IM} + \mu_{ST} - \ln pfa_0}{\sigma_{ST}} \right) \tag{11}
\]

Here, \( \phi(x) \) and \( \Phi(x) \) are the standard Gaussian probability density function (PDF) and cumulative density function (CDF), respectively.

Note that Eq. (1) can be simplified when a single action is considered.

Take action if and only if

\[
E[DF|D(t),A_1] > 0 \leftrightarrow \Phi \left( \frac{\mu_{ST} + \mu_{IM} - \ln pfa_0}{\sqrt{\sigma_{ST}^2 + \sigma_{IM}^2}} \right) > \frac{r_{C1}C1 + r_{C2}C2}{r_{d}B} \equiv P_0 \tag{12}
\]

The decision contour can then be found in closed form by solving Eq. (12) for \( \mu_{IM} \) as a function of \( \sigma_{IM} \) in the case of equality

\[
\mu_{IM} = \left( \ln pfa_0 - \mu_{ST} \right) + \sqrt{2(\sigma_{ST}^2 + \sigma_{IM}^2)} \text{erf}^{-1}(2P_0 - 1) \tag{13}
\]

Here, \( \text{erf}^{-1} \) is the inverse error function. Note that \( P_0 \) is always between 0 and 1, with \( P_0 \) approaching zero when benefit dominates cost, and action is always taken. If \( P_0 \) is greater than or equal to 1, the action is never taken because the benefit cannot cover the cost. This result illustrates the possibility of choosing the type of decision behavior that a user desires based on \( P_0 \), instead of going through a complete cost-benefit analysis that leads to a fixed decision behavior.

Fig. 5 shows the influence of \( P_0 \) on the decision contour (a method to understand how uncertainty influences decision). When \( P_0 < 0.5 \), the critical mean value of \( \ln \text{PGA} \) that separates action and no-action region decreases as uncertainty (the standard deviation) increases. The authors will stop the elevator with a smaller shaking level as the EEW information becomes more uncertain, and it represents a conservative decision behavior, which is also called uncertainty averse in the ePAD framework. On the contrary, \( P_0 > 0.5 \) represents a risk-taking decision behavior, because the authors will not stop the elevator until a higher shaking level is reached as uncertainty increases, which is also called uncertainty taking in ePAD. In this sense, \( P_0 = 0.5 \) represents an uncertainty-neutral decision behavior.

Fig. 6 shows the influence of structural model uncertainty \( \sigma_{ST} \) on the decision contour (or the decision behavior). From Eq. (13), the decision contour approaches a linear function when
\( \sigma_{ST} \) approaches zero, and the contour approaches a horizontal line when \( \sigma_{ST} \) dominates \( \sigma_{IM} \). It demonstrates that the decision is less sensitive to the \( IM \) uncertainty when \( \sigma_{ST} \) dominates.

**Closed Form Solution for Incomplete Action Model**

In the incomplete action model, the influence of insufficient lead time on decision making is investigated. This model utilizes the lead time information, \( p[T_{lead}|D(t)] \), from EEW as well. Similar to the previous section, Eq. (1) is simplified to

Take action if and only if \( E[DF|D(t), a_1] > 0 \) \( \quad \text{(14)} \)

Exploiting the separation of \( T_{lead} \) and \( IM \) in \( DF \) for the complete action model [Eqs. (6) and (7)]

\[
E[DF|D(t), a_1] = E[\beta]|D(t)|E[L_B|D(t), A_1] - E[\gamma]|D(t)|E[L_C|D(t), A_1] \quad \text{(15)}
\]

The expected values of \( \beta \) and \( \gamma \) are found by integrating \( \beta \) and \( \gamma \) with \( p[T_{lead}|D(t)] \), which is taken as log-normally distributed, with mean \( \ln \mu_T \) and standard deviation \( \sigma_T \). \( \beta_1(T_{lead}) \) and \( \gamma_1(T_{lead}) \) are shown in Fig. 4.

Let\( p[T_{lead}|D(t)] = \frac{1}{T_{lead}} \phi \left( \frac{\ln T_{lead} - \ln \mu_T}{\sigma_T} \right) \) \( \quad \text{(16)} \)

then \( E[\beta]|D(t)\) \( = \Phi \left( \frac{\ln \mu_T - \ln T_u}{\sigma_T} \right) \equiv f_\beta \) \( \quad \text{(17)} \)

and \( E[\gamma]|D(t)\) \( = \left[ 1 - r_0 \right] e^{\ln \mu_T + \sigma_T^2/2} \Phi \left( \frac{\ln T_u - \ln \mu_T - \sigma_T}{\sigma_T} \right) + r_0 \)

\( \approx f_\gamma + (1 - r_0) f_\beta \) \( \quad \text{(18)} \)

Following a similar approach to that used in the previous section with \( P_0 \) defined as in Eq. (12), Eq. (14) can be rearranged to be

\[
E[DF|D(t), a_1] > 0 \implies \Phi \left( \frac{\mu_{ST} + \mu_M - \ln p f a_0}{\sqrt{\sigma_{ST}^2 + \sigma_{IM}^2}} \right) > \left( \frac{\gamma_1 + 1 - r_0}{\beta_1} \right) P_0 \triangleq r_T P_0 \quad \text{(19)}
\]

As before, the decision contour can then be found in closed form by solving Eq. (19) in the case of equality for \( \mu_M \) as a function of \( \sigma_{IM} \)

\[
\mu_M = (\ln p f a_0 - \mu_{ST}) + \sqrt{2(\sigma_{ST}^2 + \sigma_{IM}^2)\text{erf}^{-1}(2r_T P_0 - 1)} \quad \text{(20)}
\]

If one rearranges the expression for \( r_T \) in Eq. (19), it can be found that \( r_T \geq 1 \), which means that the incomplete action model in this case introduces an amplification factor \( r_T \) for \( P_0 \) from the basic model. In other words, it always gives a more uncertainty-taking decision. This is because an incomplete action is less beneficial than taking the complete action, which leads to a higher critical \( \mu_M \) value compared to the basic model. When \( r_T P_0 \geq 1 \), the action is never taken. In practice, when the basic model suggests taking action, but the incomplete action model suggests the opposite, then a backup action is triggered instead. Such backup action should be fast to complete, but will usually come with less benefit. In this case, the backup action could be an immediate stop of the elevator at the current location.

Fig. 7 shows the value of \( r_T \) as a function of \( \mu_T \) and \( \sigma_T \). Assuming \( T_u = 2s \) and \( r_0 = 0.5 \) in Fig. 4, \( r_T \) increases exponentially as \( \mu_T \) approaches and exceeds \( T_u \) and its rate of increase reduces as the uncertainty in the lead time \( \sigma_T \) increases. On the other hand, the incomplete action model has no influence on the decision when there is sufficient lead time, where \( r_T \approx 1 \).

Fig. 8 shows the decision contours for \( \ln p f a_0 = \ln(0.5) \), \( \sigma_0 = 3.125 \), \( T_1 = 2.5s \), and \( P_0 = 0.3 \), which represents a typical building high-rise system with around 20–30 floors, and a slightly conservative decision behavior under the U.S. elevator standard. In this case, \( \mu_{ST} = 0.82 \) and \( \sigma_{ST} = 0.22 \). The parameter values for lead time models are \( T_2 = 2s \), \( r_0 = 0.5 \), \( \sigma_T = 0.2 \), and \( \mu_T \) ranges from 1 to 4 s. Note that, when \( \mu_T \) is less than 2 s,
no-decision contours are shown in the figure. This is because the action is never taken due to the lack of benefit of an incomplete action, which the backup action is taken instead when necessary. One can observe that as $\mu_T$ decreases, the decision contour deviates from the one without lead time model (same as $\mu_T$ $\approx$ 3–4 s) and becomes more uncertainty taking. Consistent with the intuition, this is due to the reduced expected benefit of an incomplete action.

**Numerical Solution for Value of Information Model Using Surrogate Model**

In the value of information model, the influence of adding extra benefit for action $a_0$ on decision making is investigated. Before directly applying a surrogate model to $\text{Vol}$, the authors first simplify the expression given for the chosen $\beta_1$ and $\gamma_1$ models in the section of incomplete action model. Since $DF(IM, T_{lead} - \Delta t, a_1) < 0$ when $T_{lead} < T_a + \Delta t$, $\max\{DF(IM, T_{lead} - \Delta t, a_1), 0\} = 0$ in this range. Hence, the $T_{lead}$ lower bound of the integral of $\text{Vol}$ can be changed to $T_a + \Delta t$ instead of $\Delta t$. Also, in this range, both $\beta_1$ and $\gamma_1$ equal 1, which leads to a separation of the double integral on $T_{lead}$ and $IM$ into two single integrals.

\[
\text{Vol} = \int_{T_a + \Delta t}^{\infty} p[T_{lead}]D(t)\,dT_{lead} \\
\times \int \max\{DF(IM, A_1), 0\}p[IM|D(t)]\,dIM \tag{21}
\]

The first integral in Eq. (21) is simply the lognormal CDF, which can be rewritten as \{\Phi[\ln(\mu_T) - \ln(T_a + \Delta t)/\sigma_T]; DF(IM, A_1) = r_BlB P(\text{DM}|IM, A_1)/(r_{C1}/C1 + r_{C2}/C2)\}. Now, one can rearrange Eq. (1) to be:

Take action if and only if

\[
E[DF|D(t), a_1] = E[L_B|D(t), a_1] - E[L_C|D(t), a_1] > \text{Vol} \tag{22}
\]

Dividing the inequality by $r_Bl_B$ leads to the following simplified expression:

Take action if and only if

\[
\Phi\left(\frac{\mu_{ST} + \mu_{IM} - \ln pfa_0}{\sqrt{\sigma_{ST}^2 + \sigma_{IM}^2}}\right) > r_T P_0 + r_{Vol} I_{Vol} \tag{23}
\]

where $r_{Vol}(\mu_T, \sigma_T) = \Phi\left[\frac{\ln(\mu_T) - \ln(T_a + \Delta t)}{\sigma_T}\right] - \Phi\left[\frac{\ln(\mu_T) - \ln T_a}{\sigma_T}\right] \tag{24}$

and $I_{Vol}(\mu_T, \sigma_T) = \int \max\{0, P(\text{DM}|IM, A_1) - P_0\} \times \phi\left(\frac{IM - \mu_{IM}}{\sigma_{IM}}\right)\,dIM \tag{25}$

Note that $r_{Vol} I_{Vol} \geq 0$, which means that the value of information model in this case increases the value of $r_T P_0$ from the incomplete action model. In other words, it always gives an even more uncertainty-taking decision. This is because the extra benefit from delaying the decision represented by $\text{Vol}$ leads to an even higher critical $\mu_{IM}$ value compared to the incomplete action model with no waiting for more EEW information. Different from this incomplete action model, $\text{Vol}$ is not only a function of $\mu_T$ and $\sigma_T$, but is also a function of $\mu_{IM}$ and $\sigma_{IM}$. This is reasonable because, for example, one is more likely to delay a decision when the EEW information is not available.

\[
T_a = 2, r_0 = 0.5
\]

**Fig. 7.** Value of $r_T$ as a function of $\mu_T$ and $\sigma_T$ given a fixed $T_a$ and $r_0$

**Fig. 8.** Decision contours with incomplete action model

**Fig. 9.** RVM surrogate model for $I_{Vol}$ as a function of $\mu_{IM}$ and $\sigma_{IM}$ ($T_1 = 2.5, P_{0CB} = 0.300000$)
very uncertain. Whereas $r_{\text{Vol}}$ can be calculated in closed form from Eq. (24), an RVM surrogate model is used to calculate $I_{\text{Vol}}$.

Fig. 9 shows an RVM surrogate model for $\ln pf\alpha_0 = \ln(0.5)$, $\alpha_0 = 3.125$, $T_1 = 2.5s$, and $P_0 = 0.3$, which are the same values as in Fig. 8. The data points for generating the surrogate model are obtained from Monte Carlo simulation (MCS) of the actual integral $I_{\text{Vol}}$. In this study, the authors generated a total of nine surrogate models [three building types: $\alpha_0 = 1,3.125,12.5$ and three elevator standards: $\ln pf\alpha_0 = \ln(0.08), \ln(0.15), \ln(0.5)$] as a function of $P_0$, $T_1$, $\mu_{IM}$ and $\sigma_{IM}$. The maximum approximation error among all models is controlled to be under 5%.

Fig. 10 shows the resulting decision contours of a specific case where $I_{\text{Vol}}$ in Eq. (23) is obtained from the RVM surrogate model and also directly from MCS based on the same parameter values as in Fig. 8 with $\Delta t = 1s$. The surrogate model estimates the actual decision contours well. Also, one can see that as $\mu_T$ increases, the decision contour becomes more uncertainty taking because of the expected benefit of the potentially less uncertain information in the future. However, comparing to Fig. 8, the larger $\sigma_{IM}$ is the larger the difference in the decision contours. This is consistent with the intuition that one will only want to delay the decision if the current information is uncertain. Note that again, when $\mu_T$ is

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**Fig. 10.** Decision contours with value-of-information model (solid line = MCS; dotted line = RVM)

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**Fig. 11.** Location of a segment of San Andreas Fault (solid black line) and a chosen building in downtown Los Angeles (star) (map data © 2013 Google, INEGI)
less than 2 s, no-decision contours are shown in the figure. This is because the action is never taken due to the lack of benefit from an incomplete action. As mentioned in the section of closed form solution for incomplete action model, the backup action is triggered when necessary.

**Example**

A segment of the San Andreas Fault (from Palmdale to San Bernardino) is selected to demonstrate the authors’ proposed application to elevator control. A building with parameters $T_1 = 2.5$ s and $\alpha_0 = 3.125$ is chosen (same values as previously used in the analyses), that is located in downtown Los Angeles. The solid black line in Fig. 11 shows the causative fault segment and the star indicates the building location.

Instead of parameterizing the PDF of $IM$ from EEW, $p[IM|D(t)]$, into $\mu_{IM}$ and $\sigma_{IM}$, the PDF is found as a function of earthquake magnitude and hypocenter-to-site distance using the ground motion prediction equation developed by Boore and Atkinson (2008). Hence, instead of plotting the decision contours in a 2D space of $\mu_{IM}$ and $\sigma_{IM}$, the contours are plotted in a 2D space of earthquake magnitude and location along the chosen segment of the San Andreas Fault. Once again, the region above the decision contour represents taking action; the region below the decision contour represents not to take action. Change of decision contours is investigated based on two factors: varying $\mu_T$ for a fixed $\ln pf a_0$; and varying $\ln pf a_0$ for a fixed $\mu_T$.

Fig. 12 shows the result of this simulation. As one would expect, the location on the fault line that is the closest to the building has the lowest critical magnitude to trigger the action, and a decrease in $\ln pf a_0$ lowers the whole-decision contour in this plot. Note that no-decision contour is shown in the plot for $\ln pf a_0 = \ln(0.5)$ (the U.S. standard) because the action is never taken within the tested range of magnitude on the chosen fault segment. This is not an intuitive result and the authors suggest that the current standard may need to be changed if a robust decision framework is to be put in place. Also, $\mu_T = 2.5$ s leads to the lowest set of values of the critical magnitude along the fault segment because after including the lead time uncertainty, this is the mean lead time that has the least influence from both incomplete action model and the value of information model because there is just enough time to perform the action (both models penalize the benefit of taking action in some way).

**Conclusion**

This study presents a decision framework for elevator control based on uncertain EEW information using the ePAD framework (Wu et al. 2013) with a suggested structural model, decision model, and lead time model. The authors’ analysis shows that instead of going through the complication of a complete structural model, a user may select the value of a related variable $P_0$ that can represent the users desired type of decision behavior. Also, the influence of lead time and EEW uncertainties on decisions can be easily understood through the use of decision contours, which represent different types of decision behaviors. A surrogate model using the machine learning algorithm RVM is created for the sake of fast computation of the value of information model. The steps to setup the algorithm for automated decisions of elevator control using uncertain EEW information are summarized by:

1. Model parameters setup: Choose $T_1$ and $\alpha_0$ based on a target building; choose $\Delta t$ and $\ln pf a_0$ based on the EEW system operation and the elevator standard for the region where the building is located; choose $T_a$ and $r_0$ based on a specific elevator application;

2. Evaluate decision contour: Pick a $P_0$ value and generate decision contours as a function of ($\mu_T$, $\gamma_T$) and ($\mu_{IM}$, $\sigma_{IM}$) or (earthquake magnitude, fault line segments); and

3. Check decision behavior: Iteratively increase or decrease $P_1$ to find a value that can best represent the user’s desired decision behavior under uncertain EEW information.

Further refinement of the models employed in ePAD for elevator control could be explored. As explained in Wu et al. (2013), more flexibility in the types of decision behavior can be obtained by adjusting $\Delta t$. Although the chosen structural model can be readily applied to various types of buildings, in order to obtain a better representation of a target building, a more sophisticated structural model can be used to replace the simpler model used in this paper. If necessary, the decision model and lead time model ($\beta_1$ and $\gamma_1$) can also be changed, at the possible expense of introducing extra complexity into the problem.

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