A decision-making methodology for risk-informed earthquake early warning

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Abstract
To maximize the potential of earthquake early warning (EEW) as a credible tool for seismic resilience promotion, it should be combined with next-generation decision-support tools that use advanced risk-based predictions and account for unavoidable malfunctions of the system (i.e., false alarms) to determine whether or not alerts/mitigation actions should be triggered. This work contributes to the required effort by developing a novel end-user-oriented approach for decision making related to very short-term earthquake risk management. The proposed methodology unifies earthquake-engineering-related performance assessment procedures/metrics (for end-user-focused damage and consequence estimation) with multicriteria decision-making tools (to consider end-user preferences toward different types of risks). It is demonstrated for EEW in a hypothetical school building, to specifically investigate the optimal decisions (i.e., “trigger”/“do not trigger” alerts) for a range of earthquake scenarios with varying parameter uncertainties. In particular, it is found that the best action for a given ground-shaking intensity can depend on stakeholder (end-user) preferences.

1 | INTRODUCTION

Earthquake early warning (EEW) is undergoing a growth in popularity worldwide as an attractive tool for enhancing and promoting seismic resilience in urban areas (e.g., Cauzzi et al., 2016; Gasparini et al., 2011). Specifically, EEW systems rely on real-time data telemetry to provide information about ongoing earthquakes, enabling various stakeholders (end-users) to take effective steps for reducing potential harmful impacts of an event before strong shaking occurs at a target site (e.g., Allen & Melgar, 2019; Hsu et al., 2016; Panakat & Adeli, 2008; Rafiei & Adeli, 2017; Satriano, Wu et al., 2011). This type of technology is currently operating in nine countries, and is being tested for feasibility in many more (Cremen & Galasso, 2020; Cremen et al., 2021).

To date, innovations in EEW have largely focused on seismological aspects and hazard models. For example, one of the most recent advances in EEW is the use of machine learning to discriminate seismic signals from noise, for more reliable earthquake detection (Meier et al., 2019). However, to maximize the potential of these technologies as effective risk-management tools, there also needs to be a focus on developing and incorporating next-generation decision-support tools. These tools use advanced engineering-based consequence predictions related to the corresponding hazards, so that stakeholders can be informed of appropriate risk mitigation actions to
take when necessary (e.g., Bozza et al., 2017; Ouyang & Fang, 2017; Sharma et al., 2020; Tesfamariam et al., 2010; Zhou et al., 2018).

Some work connected to this requirement has already been done in the literature. For example, Grasso (2005), Iervolino, Giorgio et al. (2007), and Iervolino (2011) introduced a probabilistic loss-driven decision-making framework for EEW. This was advanced in Wu et al. (2013) through the integration of basic decision theory, and the updated methodology was applied to the automated process of elevator control in Wu et al. (2016). Additional examples of EEW risk-based decision-making procedures proposed in the literature are those documented in Grasso et al. (2007), Salzano et al. (2009), Wang et al. (2012), and Le Guenan et al. (2016).

However, most of the aforementioned studies rely on the concept of equally weighted cost–benefit analysis and/or only one loss-related criterion to support decision making. These types of approaches have several disadvantages. First, cost–benefit analyses require the use of questionable assumptions about the dollar value of nonmonetary losses (such as casualties and functional disruption), which may not be accurate and can lack consistency across different jurisdictions (e.g., Krawinkler et al., 2006; Viscusi & Masterman, 2017). Second, these approaches do not (or do not easily) enable different dimensions of risk (e.g., public safety, economic loss, and functionality) to be distinguished in the decision-making process, which is problematic if the stakeholder does not place equal importance on each risk type (May, 2004). Third, they do not account for risk tolerance, which is an important consideration for engineering-related applications (Stewart & Melchers, 1997). While the work of Wu et al. (2013) leverages expected utility theory in an attempt to overcome this final limitation, the basis of their decision-making procedure remains a cost–benefit analysis. As a further improvement, Le Guenan et al. (2016) use multiattribute utility theory applied to various risk-tolerance scenarios, which theoretically eliminates all of the above restrictions. But the proposed methodology only works for binary action cases (e.g., “trigger” or “do not trigger” an EEW alarm), uses a simplistic time-independent description of real-time seismic hazard, and relies on a deterministic engineering-agnostic damage-to-loss relationship, which make it unsuitable for a broad range of short-term seismic risk management purposes.

This paper proposes an advanced methodology that overcomes all of the previously identified shortcomings in two main ways. First, it implements a general multi-criteria decision-making (MCDM) approach, which enables multiple mitigation actions to be evaluated for various dimensions of uncertain risk. The particular MCDM technique discussed in the paper has been successfully implemented in previous work to determine optimal seismic retrofitting options (Caterino et al., 2008, 2009; Gentile & Galasso, in press) and more general emergency response solutions (Zhang et al., 2016), for example. Second, MCDM is coupled with a modified version of the performance-based earthquake engineering (PBEE) framework (Moehle & Deierlein, 2004) that incorporates evolutionary Bayesian real-time seismic hazard analysis. This framework forms a convenient mathematical foundation for real-time probabilistic seismic risk decision making that (1) accounts for all important sources of uncertainty associated with EEW and (2) considers multiple consequence variables. Furthermore, traditional PBEE has been used to choose optimal actions in many other earthquake-engineering-related applications, such as seismic design (Goda & Hong, 2006), seismic retrofitting (Porter et al., 2006), seismic sensor implementation (Cremen & Baker, 2018), postearthquake repair scheduling (Xiong et al., 2020), and parametric earthquake insurance (Goda, 2015), as well as MCDM problems involving household recovery (Burton et al., 2018) and design optimization (Mosalam et al., 2018; Saadat et al., 2014).

This paper is organized in the following manner. The proposed methodology is developed within Section 2, which specifically details how MCDM and PBEE are uniquely unified in the context of risk-driven EEW. Section 3 involves an application of the methodology to EEW in a hypothetical school, and the optimal decision is investigated for various levels of information on the incoming earthquake. Finally, discussion and conclusions on the study are provided in Section 4.

2 | METHODOLOGY

The proposed methodology consists of a number of well-defined, computer-implementable steps (i.e., algorithm). It evaluates a group of end-user selected EEW mitigation actions \( \{A_i\} \), as well as the option of taking no action \( \bar{A} \), based on case-specific values associated with a set of corresponding uncertain consequence criteria \( \{C_j\} \) that are assigned weights \( \{w_j\} \) to reflect their importance in line with end-user preferences. The explicit incorporation of these preferences and the fact that the criteria do not need to be given a monetary value both represent improvements over conventional dollar-based (cost–benefit) decision-making procedures used in past EEW studies, as discussed in the previous section. The methodology is comprised of three main steps. The first step represents the real-time PBEE module of the algorithm (Mod_PBEE), which computes the probabilistic consequences \( \{C_j\} \) for each action and uses an evolutionary seismic hazard analysis to facilitate the integration with existing seismological
algorithms for EEW. The second step integrates the outputs of Mod_PBEE within the MCDM module (Mod_MCDM), which accounts for the criteria-specific risk priorities of stakeholders \(\{w_j\}\). The results of Mod_MCDM are used to select the optimal decision in the final step of the methodology (Mod_Decision).

**Step 1: Develop a consequence matrix (Mod_PBEE).** For all \(N_a\) identified actions and \(\bar{A}\), the values associated with each of the \(N_c\) consequence criteria are first assembled in a consequence matrix (see Table 1—note that the criteria shown are merely representative and do not constitute an exhaustive list). The value of the \(j\)th criterion for \(\bar{A}\) is equivalent to the expected value of the consequence \(E\bar{A}(C_j^\bar{A}|d)\) for the incoming ground shaking. \(E\bar{A}(C_j^\bar{A}|d)\) is estimated using PBEE theory and physical measurements from a network of seismic stations \(\{d\}\), according to the performance-based earthquake early warning (PBEEW) framework developed by Grasso (2005) and Iervolino, Giorgio et al. (2007):

\[
E\bar{A}(C_j^\bar{A}|d) = \int_{C_j^\bar{A}} \int_d \int_{im} \bar{A}_j f(\bar{A}_j|d) f(d|m) f(m|im) \, d\bar{A}_j \, dm \, ddim \tag{1}
\]

\[
f(a|b)\) is the probability density function (pdf) of \(a\) conditional on \(b\), \(dm\) is a scalar or vector measure of damage level, and \(\text{im}\) is a vector of ground shaking intensities. \(f(d|m|im)\) can be obtained using a building-level fragility function (scalar damage) or through an intermediate engineering demand/structural response parameter \((EDP)\) variable for component-level performance assessment procedures (vector damage); in the latter case, \(f(d|m|im) = \int_{EDP} f(d|edp) f(\text{edp}|im) \, d\text{EDP}\).

\(f(\text{im}|d)\) is the pdf of \(\text{im}\) given current knowledge on the incoming event. \(d\) could comprise the vectors of information used by the implemented seismological EEW algorithm—for example, ElarmS (Brown et al., 2011) or PRESTo (Satriano, Elia et al., 2011)—to estimate magnitude and location in real time. If the applicable seismological algorithm provides point estimates of the magnitude \((\hat{m})\) and location of the incoming event, then \(d = \{\hat{m}, \hat{r}\}\) (where \(\hat{r}\) is the corresponding estimate of the distance from the source to a target site of interest) and:

\[
f(\text{im}|d) = f(\text{im}|\{\hat{m}, \hat{r}\}) \tag{2}
\]

can be computed with the aid of a ground motion model (GMM), for example. Where the seismological algorithm uses the seismic network measurements to estimate the incoming ground shaking at a site \((\text{im}\), \(d = \text{im}\) and \(E\bar{A}(C_j^\bar{A}|d)\) is found using the following simplified version of Equation (1):

\[
E\bar{A}(C_j^\bar{A}|d) = E\bar{A}(C_j^\bar{A}|\text{im}) = \int_{C_j^\bar{A}} \int_d \int_{im} \bar{A}_j f(\bar{A}_j|d) f(d|m|im) \, d\bar{A}_j \, dm \, ddim \tag{3}
\]

It can be seen from Table 1 that the expected value of the \(j\)th criterion for the \(i\)th action, \(E\bar{A}_i(C_j^\bar{A}|d)\) includes (1) the consequence associated with a potential false alarm, \(E(C_{jF}^A|d)\), as well as (2) the action-, criterion-, and

| Table 1: Explanation of consequence matrix inputs for Step 1 of the proposed methodology |
|---------------------------------------------------------------|
| **A_1** | **C_2** | **C_3** |
| **A_1** | **Casualties (Number)** | **Downtime (days)** | **Direct cost ($)** |
| **A_1** | Expected casualties from possible false alarm + expected casualties from estimated shaking that is not eliminated with mitigation action 1, \([E^{A_1}(C_1^A|d)]\) | Expected disruption from possible false alarm + expected downtime from estimated shaking that is not eliminated with mitigation action 1, \([E^{A_1}(C_2^A|d)]\) | Expected reconditioning cost from possible false alarm + expected repair cost from estimated shaking that is not eliminated with mitigation action 1, \([E^{A_1}(C_3^A|d)]\) |
| \(\cdots\) | \(\cdots\) | \(\cdots\) | \(\cdots\) |
| \(\cdots\) | \(\cdots\) | \(\cdots\) | \(\cdots\) |
| **A_{N_a}** | Expected casualties from possible false alarm + expected casualties from estimated shaking that is not eliminated with mitigation action \(N_a\), \([E^{A_{N_a}}(C_{N_a}^A|d)]\) | Expected disruption from possible false alarm + expected downtime from estimated shaking that is not eliminated with mitigation action \(N_a\), \([E^{A_{N_a}}(C_{N_a}^A|d)]\) | Expected reconditioning cost from possible false alarm + expected repair cost from estimated shaking that is not eliminated with mitigation action \(N_a\), \([E^{A_{N_a}}(C_{N_a}^A|d)]\) |
| \(\bar{A}\) (no action) | Expected casualties from estimated shaking, \([E^\bar{A}(C_1^\bar{A}|d)]\) | Expected downtime from estimated shaking, \([E^\bar{A}(C_2^\bar{A}|d)]\) | Expected repair cost from estimated shaking, \([E^\bar{A}(C_3^\bar{A}|d)]\) |
event-specific proportion of the corresponding PBEE-based consequence for $\bar{A}$ that cannot be mitigated, $E(\bar{A}^r_i|d)\kappa_{ij}(d)$ (where $\kappa_{ij}(d)$ is a scalar value between 0 and 1). False alarms occur when a risk-mitigation action turns out to be unnecessary for the level of shaking actually observed, that is, when no vulnerable component in the building (either structural or nonstructural) is damaged. The probability of a false alarm, $p(FA|d)$, may be calculated as follows:

$$p(FA|d) = (1 - p(Cp|d)) \left(1 - \int_{dm} f(dm||d, \bar{Cp}) dm\right)$$  \hspace{1cm} (4)

where $Cp$ is the occurrence of collapse and $\bar{Cp}$ is its complementary. $E(C_{ij}^F A|d)$ is then computed using the following equation:

$$E \left( C_{ij}^F A \| d \right) = e_{ij}^F \cdot p(FA|d)$$  \hspace{1cm} (5)

where $e_{ij}^F$ is the expected consequence due to false alarm disruption for the $j$th criterion and the $i$th action. Both $c_{ij}^F A$ and $\kappa_{ij}(d)$ are obtained from stakeholder feedback.

Examples of potential EEW actions for a building include: $A_1$: “duck, cover, and hold” (DCHO) and $A_2$: “evacuate the building.” $A_1$ will likely lead to longer expected casualties for an incoming event than $A_2$, since DCHO will not protect occupants if the building collapses. However, $A_2$ requires a disruptive (and potentially costly) period of building reoccupation in the event of a false alarm, which is avoided for $A_1$. Potential EEW actions for a bridge include: $A_1$: “shut the bridge” and, based on the work of Maddaloni et al. (2011), $A_2$: “keep the bridge open, using semi-active control strategies to optimize its real-time structural response.” Here, $A_1$ will result in lower shaking-related—but higher false-alarm-related—consequences than $A_2$, overall. The correct action to take for any structural type will depend on stakeholder preferences toward specific types of consequences, which are accounted for in Step 2 of the algorithm.

**Step 2: Develop a decision matrix (Mod_MCDM).**

The consequence matrix values from Mod_PBEE are first normalized as follows:

$$r_{Ai, C_{ij}} = \frac{E^A_i \left( C_{ij}^A \| d \right)}{\sqrt{\sum_{k=1}^{N_a} \left( E^A_k \left( C_{ij}^A \| d \right) \right)^2} + \left( E^A \left( C_{ij}^A \| d \right) \right)^2}$$  \hspace{1cm} (6)

where $r_{Ai, C_{ij}}$ is the normalized value of the $j$th criterion for the $i$th action, and all other variables are as defined for Mod_PBEE. $r_{Ai, C_{ij}}$ values are then weighted according to stakeholder preferences (priorities) toward each criterion, to form the decision matrix (Table 2).

The corresponding weights ({$w_j$}) may be obtained using the analytic hierarchy process (Saaty, 1980) for example. This procedure involves the stakeholder performing a series of pairwise comparisons for each criterion, based on qualitative phrasing for relative importance that is quantified (for analysis purposes) on a scale from 1/9 to 9. One on the quantitative scale implies that the stakeholder considers both criteria to be equally significant, 5 indicates that the stakeholder believes criterion X is strongly important over criterion Y, 9 means that criterion X has extreme importance to the stakeholder compared to criterion Y, all other values between 1 and 9 signify intermediate judgments to those stated, and reciprocal values indicate equivalent opinions of criterion Y compared to criterion X. The quantitative results of the comparison are summarized in an $N_c \times N_x$ matrix, the principal right eigenvector of which is equivalent to {$w_j$}.

**Step 3: Identify the optimal decision (Mod_Decision).**

The final part of the methodology determines the optimal decision among {$A_i$} and $\bar{A}$. This first involves quantifying the best and worst values for each criterion across all possible options. Since the criteria in this case are negative consequences, the best value of the $j$th criterion ($u_j^+$) is its minimum value, that is, $u_j^+ = \min_j (r_{Ai, C_{ij}} w_j, \ldots, r_{A_{N_a}, C_{ij}} w_j, r_{\bar{A}C_{ij}} w_j)$ and the worst value ($u_j^-$) is its maximum, that is, $u_j^- = \max_j (r_{Ai, C_{ij}} w_j, \ldots, r_{A_{N_a}, C_{ij}} w_j, r_{\bar{A}C_{ij}} w_j)$. The total distance of a given action $A_i$ from the best ($y_i^+$) and worst ($y_i^-$) solutions are then, respectively, calculated as

\[ y_i^+ = \sum_{j=1}^{N_c} w_j \cdot u_j^+ \]  \hspace{1cm} (7)

\[ y_i^- = \sum_{j=1}^{N_c} w_j \cdot u_j^- \]  \hspace{1cm} (8)

TABLE 2 Sample decision matrix developed in Step 2 of the proposed methodology

| Action | $C_1$ Casualties (Number) | $C_2$ Downtime (days) | $C_3$ Direct cost ($) |
|--------|---------------------------|-----------------------|-----------------------|
| $A_1$  | $r_{Ai, C_{ij}} w_j$     | $r_{Ai, C_{ij}} w_j$ | $r_{Ai, C_{ij}} w_j$ |
| …     | …                        | …                     | …                     |
| $A_{N_a}$ | $r_{A_{N_a}, C_{ij}} w_j$ | $r_{A_{N_a}, C_{ij}} w_j$ | $r_{A_{N_a}, C_{ij}} w_j$ |
| $\bar{A}$ (no action) | $r_{\bar{A}C_{ij}} w_j$ | $r_{\bar{A}C_{ij}} w_j$ | $r_{\bar{A}C_{ij}} w_j$ |
follows:

\[ y_i^+ = \sqrt{\frac{\sum_{j=1}^{N_c} \left( u_j - (r_{A_iC_j} \cdot w_j) \right)^2}{\sum_{j=1}^{N_c} (u_j - (r_{A_iC_j} \cdot w_j))^2}} \]

(7)

\[ y_i^- = \sqrt{\frac{\sum_{j=1}^{N_c} \left( v_j - (r_{A_iC_j} \cdot w_j) \right)^2}{\sum_{j=1}^{N_c} (v_j - (r_{A_iC_j} \cdot w_j))^2}} \]

(8)

The optimal action is the one with the largest \( S_i \) value, calculated according to:

\[ S_i = \frac{y_i^-}{y_i^+ + y_i^-} \]

(9)

Note that the final two steps have specifically been described in terms of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach (Caterino et al., 2009; Yoon & Hwang, 1995), which is adopted in the case-study application (Section 3). However, the risk attitudes of stakeholders could additionally be explicitly accounted for by alternatively using multiattribute utility theory (Dyer, 2005), without changing the overall structure of the system. In that case, the \( r_{A_iC_j} \) values of the decision matrix in Step 2 would be replaced with normalized utility values \( u_{A_iC_j} \) that depend on the values of the consequence matrix and the risk tolerance of stakeholders. \( u_{A_iC_j} \) would then be aggregated across each option (either additively or multiplicatively), and the optimal decision would be the one that maximizes the final value.

The developed algorithm is provided in Appendix A. This algorithm could be packaged as a state-of-the-art risk-driven plug-in to existing EEW platforms, providing operational EEW with high-resolution structure-specific decision-making capabilities for the first time. The computational assimilation of the plug-ins and the seismology-focused algorithms of the current platforms would be facilitated by the PBEEW architecture, outlined in Equation (1).

3 | EXAMPLE APPLICATION TO A SCHOOL BUILDING

The proposed methodology is now demonstrated, using a hypothetical school located in Palo Alto, California (37.4° North and 122.15° West). The choice of location is timely, given that California is beginning to benefit from public alerts issued by the ShakeAlert EEW system (e.g., McBride et al., 2020). This system combines point-source and finite-source algorithms, to create an alert for incoming earthquakes with estimated magnitudes of at least 4.5 (e.g., Chung et al., 2020). A hypothetical school is chosen for the following reasons: (1) The examined consequence weighting scenarios may not accurately reflect the priorities of actual decision makers in a real school, posing an ethical challenge; (2) It enables the general applicability of the method to be emphasized, demonstrating that it is not just limited to one particular building or even one specific structural/occupancy type; and (3) The ShakeAlert EEW system does not (yet) facilitate building-specific public EEW alarms, making it impossible to apply the methodology to a real Californian building equipped with EEW.

While it is possible to consider multiple actions using the proposed methodology (as discussed in Sections 1 and 2), it is assumed that there are only two potential risk-management options for this particular case study: “Trigger the EEW alarm” (1) and “Don’t trigger the EEW alarm” (2). The target structure of interest is assumed to be a two-story reinforced concrete moment-resisting frame with column-beam connections, in line with typical characteristics of suburban U.S. schools (FEMA, 2010; The National Institute of Building Sciences, 2010). The plan layout of the two-story precast concrete frame school detailed in O’Reilly et al. (2018) is adopted, assuming a story floor height of 4 m (13 feet) and a total height of 8 m (26 feet). Additional details on the building model are provided in Appendix C.

Casualties, downtime, and direct cost are selected as the consequence criteria, which are the traditional performance metrics considered in PBEE (Moehle & Deierlein, 2004). \( E^2(C^2[d]) \) values are obtained using the component-level FEMA P-58 seismic performance assessment procedure for individual buildings (FEMA, 2018). The FEMA P-58 simplified structural analysis procedure is used, which determines engineering demand as a function of peak ground acceleration (PGA) and spectral acceleration at the building’s fundamental period \( (S_a(T_1)) \), that is, \( im = \{PGA, S_a(T_1)\} \) in Equation (1). Additional information on the inputs to FEMA P-58, including the structural and nonstructural components modeled, are provided in Appendix C.

It is assumed that a false alarm does not cause any casualties, results in disruption equivalent to 5% of a day (i.e., 1.2 h—to reorganize classes and ease panicked students), and costs $200 for a structural engineering inspection to verify that no damage has occurred. It is assumed that an alarm eliminates any casualties and laptop (i.e., component “UD” in Appendix C) breakages that are not caused by the building collapsing. A general event-independent consequence matrix for the case study is presented in Table 3.

To reflect a diverse range of potential stakeholder priorities toward the different consequence criteria, the following sets of \( \{w_j\} \) values in Table 2 are examined: (1)
TABLE 3 Consequence matrix for the case study EEW application, expressed as a function of generic event parameters, \( d, \alpha_{11}(d) \) accounts for collapse casualties. Both \( c_{12}(d) \) and \( c_{13}(d) \) account for collapse laptop breakages (i.e., failure of component “UD” in Appendix C). \( r_{13} = 0.05 \) and \( r_{11} = 200 \) in line with the false alarm assumptions outlined in Section 3.

| \( C_i \) | Casualties (Number) | \( C_2 \) | Downtime (days) | \( C_3 \) | Direct cost ($) |
|----------|---------------------|----------|-----------------|----------|----------------|
| \( A_1 \) = Trigger alarm | \( E^3(C^3_1)(d)\alpha_{11}(d) \) | 0.05 \( p(FA|d) + E^3(C^3_2)(d)\alpha_{12}(d) \) | 200 \( p(FA|d) + E^3(C^3_3)(d)\alpha_{13}(d) \) |
| \( A \) = Don’t trigger alarm | \( E^3(C^3_2)(d) \) | \( E^3(C^3_3)(d) \) | \( E^3(C^3_3)(d) \) |

\( w_1 = w_2 = w_3 = 0.333 \) (i.e., a stakeholder has equal preference for all criteria); (2) \( w_1 = 0.5 \) and \( w_2 = w_3 = 0.25 \) (i.e., a stakeholder has higher preference for mitigating casualties); (3) \( w_2 = 0.5 \) and \( w_1 = w_3 = 0.25 \) (i.e., a stakeholder has higher preference for mitigating downtime); and (4) \( w_3 = 0.5 \) and \( w_1 = w_2 = 0.25 \) (i.e., a stakeholder has higher preference for mitigating direct costs). Sections 3.1–3.3 investigate the optimal EEW triggering decision, using three different types of information for estimating \( E^3(C^3_3)(d) \).

Note that the proposed approach is not compared with previous EEW decision-making methodologies discussed in Section 1, since this would require: (1) tenuous assumptions about the dollar value of downtime and casualties or (2) simplified building-level fragility models and deterministic damage-to-loss relationships, which are not compatible with the advanced PBEE approach of our study. In both cases, discrepancies in the final results would arise due to the loss or damage assumptions required as well as because of the different decision-making approaches adopted, leading to unfair comparisons.

### 3.1 Optimal decision as a function of ground shaking

The optimal decision is first examined for a given level of ground shaking, to determine how often the EEW alarm is triggered. This analysis is mathematically equivalent to a case in which the seismological algorithm accurately estimates the shaking intensity at the site. Therefore, this examination uses \( E^3(C^3_3)(d) \) values computed according to Equation (3), for \( \bar{m} = \bar{m} \). 2018 US National Seismic Hazard Model (Petersen et al., 2020) site-specific hazard curves are used (for site class D, in line with the soil properties discussed in Section 3.2). A uniform hazard approach is adopted to determine the frequency at which the examined shaking levels (i.e., \( Sa(T_1) \leq 0.3g \)) are exceeded.

Figure 1 displays the results of this analysis. As expected, the optimal decision for small shaking intensities is \( \bar{A} \) due to the low potential for damage at these levels and therefore the high probability of a false alarm. The intensity at which using the alarm becomes the optimal decision depends on stakeholder preferences. It is triggered as low as \( Sa(T_1) = 0.12g \) (or approximately once every 10 years on average) when casualties are prioritized, which is partly explained by the assumption of no casualty consequences for a false alarm. However, it is only triggered for \( Sa(T_1) \) values in excess of 0.22g (i.e., approximately once every 20 years on average) when downtime is treated as the most important risk criterion. Variation in the optimal decision for different criteria weighting is a notable finding, which confirms the importance of accounting for stakeholder preferences when designing a decision-support tool for earthquake risk management.

### 3.2 Optimal decision as a function of magnitude and distance estimates

Optimal actions for incoming earthquakes are now investigated, assuming that the seismological algorithm provides accurate estimates of magnitude and epicentral location. Thus, \( E^3(C^3_3)(d) \) values are computed using Equations (1) and (2), for \( \{\bar{m}, \bar{f}\} = \{m, r\} \) (where \( r \) is the true epicentral distance value).

Given the focus on scenario events in this case, \( f(\bar{m}[\{m, r\}]) \) is computed according to the conditional mean spectrum approach proposed by Baker and Cornell (2005, 2006). \( f(Sa(T_1)|\{m, r\}) \) is first determined using the
GMM proposed by Boore et al. (2014) for Western U.S. shallow crustal seismicity and assuming strike-slip faulting to reflect the style of the seven most prominent Bay Area faults. This model requires a rupture distance measure \( r_{JB} \) as input. \( r \) is converted to \( r_{JB} \) using adjustment factors provided in Thompson and Worden (2018) for strike-slip faulting in active crustal regions. Uncertainty in the conversion is accounted for by amplifying the standard deviation of the GMM as suggested by the authors. The shear-wave velocity input of the GMM (i.e., \( V_{s30} \)) is set equal to 352.1 m/s, which is the value recorded closest to the chosen site in the compilation of \( V_{s30} \) measurements prepared by Yong et al. (2015). The correlation model of Baker and Jayaram (2008) is then used to find the conditional distribution of \( PGA \), that is, \( f(PGA|Sa(T_1),\{m,r\}) \), according to eqs. 13 and 14 of Baker and Cornell (2005).

3.3 | Optimal decision as a function of EEW parameters

The ElarmS EEW algorithm (Brown et al., 2011) is adopted for this example, which is part of the point-source code used in the ShakeAlert system. It is therefore assumed that \( d \) consists of the peak displacements measured during the first 4 s of the P-wave recorded at each station \( P_{d_j} \), which introduces uncertainty in the magnitude prediction of the EEW system (note that distance uncertainty is neglected, since it is negligible with respect to that of magnitude and ground shaking; Iervolino et al., 2009). In this case, Equation (1) simplifies to:

\[
E\widetilde{A} \left( C_j | d \right) = \int_M E\widetilde{A} \left( C_j | m, r \right) f(m|d) dM \tag{10}
\]

where the value of \( E\widetilde{A} \left( C_j | m, r \right) \) is taken directly from the analyses of Section 3.2. \( f(m|d) \) is assumed to follow the Bayesian mathematical formulation for real-time magnitude estimation proposed by Iervolino, Galasso et al. (2007). Thus, for \( N_s \) peak displacement measurements:

\[
f(m|d) = f(m|P_{d_1}, P_{d_2}, ..., P_{d_{N_s}}) = \frac{f(P_{d_1}, P_{d_2}, ..., P_{d_{N_s}} | m) f(m)}{\int_{M_{min}}^{M_{max}} f(P_{d_1}, P_{d_2}, ..., P_{d_{N_s}} | m) f(m) dm} \tag{11}
\]

where \( f(P_{d_1}, P_{d_2}, ..., P_{d_{N_s}} | m) \) is the joint conditional pdf of the measurements (i.e., the likelihood function) and \( f(m) \) is the prior pdf of the magnitude.

\( f(m) \) is based on the Gutenberg–Richter relationship, that is:

\[
f(m) = \frac{\beta e^{-\beta m}}{e^{-\beta M_{min}} - e^{-\beta M_{max}}} \tag{12}
\]
where $M_{min}$ and $M_{max}$ are, respectively, the minimum and maximum magnitudes considered, $\beta = b/\log_{10}(e)$, and $b$ is the slope of the Gutenberg–Richter magnitude–frequency relation. $M_{min}$ is set as 4, $M_{max} = 7.5$, which is approximately equal to the modal maximum magnitude for Western United States shallow crustal seismicity implemented in Petersen et al. (2014). $b = 0.8$, that is, the relevant regional value used in Petersen et al. (2020). In line with Iervolino, Galasso et al. (2007), it is assumed that the station measurements are independent and identically distributed lognormal random variables, such that the conditional pdf of the peak displacement measured at the $k$th station may be expressed as:

$$f(P_{d_k}|m) = \frac{1}{\sqrt{2\pi}\sigma_{\ln(P_d)}} e^{-\frac{1}{2}\left(\frac{\ln(P_{d_k}) - \mu_{\ln(P_d)}}{\sigma_{\ln(P_d)}}\right)^2}$$  \hspace{1cm} (13)$$

and the likelihood function for measurements across $N_s$ stations is

$$f(P_{d_1}, P_{d_2}, \ldots, P_{d_{N_s}}|m) = \prod_{k=1}^{N_s} f(P_{d_k}|m)$$  \hspace{1cm} (14)$$

The parameters of the lognormal distribution are provided by the work of Wurman et al. (2007), which determines the magnitude–scaling relationship of the ElarmS algorithm for Northern California. Therefore:

$$\mu_{\ln(P_{d_k})} = \frac{1}{1.04\log_{10}(e)} [m - 1.27\log_{10}(r_k) - 5.16]$$  \hspace{1cm} (15)$$

where $r_k$ is the epicentral distance to the $k$th station, and

$$\sigma_{\ln(P_d)} = \frac{0.3}{\log_{10}(e)}$$  \hspace{1cm} (16)$$

based on a visual inspection of the data shown in Figure 3a of the aforementioned paper.

Using Equations (11)–(15), it can be shown that (see Appendix B for full details):

$$f(m|\mathbf{d}) = \frac{x(\mathbf{d})}{\int_{M_{min}}^{M_{max}} x(\mathbf{d}) e^{-\beta m} dm} e^{-\beta m}$$  \hspace{1cm} (17)$$

for

$$x(\mathbf{d}) = x_1 m [2d_1 - N_s x_1 m + 2x_2 (x_2 d_2 + N_s x_3)]$$  \hspace{1cm} (18)$$

where $x_1 = \frac{1}{1.04\log_{10}(e)}$, $x_2 = 1.27$, $x_3 = 5.16$, $d_1 = \sum_{k=1}^{N_s} \ln(P_{d_k})$, $d_2 = \sum_{k=1}^{N_s} \log_{10}(r_k)$, and all other variables are as defined previously. The convenience of this formulation is noteworthy; $d_1$ and $d_2$ (and therefore $E(x(\mathbf{d})|\mathbf{im})$) can be precomputed offline for all possible values of $P_{d_k}$, $r_k$, and $N_s$, to facilitate efficient real-time decision making.

The accuracy of the optimal decision predicted as a function of $P_{d_k}$, $r_k$, and $N_s$ is now investigated, for simulated events at the location of the 1989 Loma Prieta temblor (37.04° North and 121.88° West), across three case-study sites for the hypothetical school (see Figure 3): (1) the aforementioned site in Palo Alto (PA); (2) a site in San Francisco (SF); and (3) a site in San Jose (SJ). To calculate $E(x(\mathbf{d})|\mathbf{im})$, $V_s30$ is assumed to be 224.7 m/s for SF and 234 m/s for SJ, which are the closest measurements recorded by Yong et al. (2015).

The following scenario earthquakes are specifically examined: (1) $m = 5.5$; (2) $m = 6$; and (3) $m = 6.9$ (i.e., the magnitude of the real Loma Prieta event). For each of these events, Equation (13) is used to simulate 2000 $P_{d_k}$ values at a given seismic station, and therefore 2000 values of $d_1$. Using broadband and strong-motion instrument locations of the Northern California Seismic Network (NCEDC, 2014), the optimal decision is determined when all seismic stations within (a) 10 km; (b) 20 km; (c) 30 km; and (d) 50 km of the earthquake have triggered (Figure 3), which, respectively, corresponds to (a) 4; (b) 13; (c) 29; and (d) 81 triggered stations.

Figure 4 contains summary results of these analyses for PA, SF, and SJ (i.e., the average proportion of the four weighting cases investigated for which a correct decision is obtained, across the 2000 magnitude-dependent sets of simulated EEW parameters), as a function of the simulated magnitudes. Before interpreting the findings, the lead (warning) time available for the different triggered station cases is additionally considered, which is approximated at a given site according to:

$$\text{Lead time at site } t = \left(\frac{r^2 + d_{\text{hypto}}^2}{V_s} - \sqrt{\frac{r^2 + d_{\text{hypto}}^2}{V_p}} - \delta_t\right)$$  \hspace{1cm} (19)$$

$r_l$ is the site epicentral distance, $d_{\text{hypto}}$ is the depth of the earthquake, $V_s$ is the average S-wave velocity, $r_{\text{trigger}}$ is the epicentral distance to the furthest triggered station within the radius of interest, $V_p$ is the average P-wave velocity, and $\delta_t$ is a delay time that accounts for data telemetry and the time window of information required by EEW algorithms to compute source parameter estimates. $V_p = 6$ km/s and $V_p/V_s = 1.73$ are assumed, according to the 1-D P-wave model and the velocity ratio used in Lin et al. (2010), respectively. $d_{\text{hypto}} = 19$ km, that is, the true depth of the 1989 Loma Prieta event. $\delta_t$ is taken as 4 s, in line with
**FIGURE 3** Maps displaying the simulated event for the sites considered in Section 3.3, when the incoming P-waves have triggered (a) 4, (b) 13, (c) 29, and (d) 81 stations.

**FIGURE 4** Average proportion of the four sets of \( \{w_j\} \) considered for which a correct decision is predicted by the Section 3.3 algorithm at the (a) PA site, (b) SF site, and (c) SJ site, as a function of the three simulated events examined and computed using data from different numbers of triggered stations.
TABLE 4  Available lead times at examined sites, for simulated earthquakes at the location of the 1989 Loma Prieta event and different radii of triggered stations. Also shown are possible risk-mitigation actions that can be taken in the corresponding warning time, which are adapted from previous work (Goltz, 2002; Iervolino, Galasso et al., 2007; Iervolino, 2011; Oliveira et al., 2015; Porter, 2016; Gobbato et al., 2017).

| Triggered station radius | Site | Lead time (s) | Possible actions |
|--------------------------|------|---------------|------------------|
| 10 km                    | PA   | 6.9           | Performing "drop, cover, and hold on"; Stopping and opening elevators at the nearest floor; Shutting off gas; Shutting down school lab equipment; Evacuating building ground floors. |
|                          | SF   | 15.4          | Finding a safe place in an adjacent room; Shutting down industrial equipment; Controlling production lines; Directing traffic away from underpasses; Stopping surgical procedures; Removing vehicles from garages. |
|                          | SJ   | 2.4           | Finding a safe place a few steps away; Switching traffic lights to red; Switching on semiactive control systems for structures. |
| 20 km                    | PA   | 5.9           | Performing "drop, cover, and hold on"; Stopping and opening elevators at the nearest floor; Shutting off gas; Shutting down school lab equipment; Evacuating building ground floors. |
|                          | SF   | 14.4          | Finding a safe place in the same room; Shutting down industrial equipment; Controlling production lines; Directing traffic away from underpasses; Stopping surgical procedures; Removing vehicles from garages. |
|                          | SJ   | 1.4           | Finding a safe place a few steps away; Switching traffic lights to red; Switching on semiactive control systems for structures. |
| 30 km                    | PA   | 4.6           | Finding a safe place a few steps away; Switching traffic lights to red; Switching on semiactive control systems for structures. |
|                          | SF   | 13.1          | Finding a safe place in the same room; Shutting down industrial equipment; Controlling production lines; Directing traffic away from underpasses; Stopping surgical procedures; Removing vehicles from garages. |
|                          | SJ   | 0.1           | —                |
| 50 km                    | PA   | 1.6           | Finding a safe place a few steps away; Switching traffic lights to red; Switching on semiactive control systems for structures. |
|                          | SF   | 10.1          | Finding a safe place in the same room; Shutting down industrial equipment; Controlling production lines; Directing traffic away from underpasses; Stopping surgical procedures; Removing vehicles from garages. |
|                          | SJ   | −2.9          | —                |

It can be seen in Figure 4 that the accuracy of the predicted optimal action based on precomputed EEW parameters can depend on the magnitude of the incoming earthquake. For example, in the case of SF and a triggered station radius of 10 km, the correct action (i.e., A₁) is predicted for all weighting cases across all 2000 sets of simulated EEW parameter values for \( m = 6.9 \), but many sets of simulated EEW parameter values incorrectly predict this action for \( m = 5.5 \). This may be explained by the fact that the true optimal action at SF is constant for all magnitudes close to \( m = 6.9 \) (and therefore for all \( d \) likely to be observed for this event), whereas the true optimal action switches from \( A \) to \( A₁ \) at magnitudes close to \( m = 5.5 \) for all weighting cases. Second, as expected, the accuracy of the system increases as more stations are triggered and estimates of the magnitude stabilize. For the specific events and sites examined here, this means that the average accuracy of predicted optimal decisions improves from 79% when four stations are triggered to 100% when 81 stations are triggered. Finally, it is important to note that high accuracy is achieved sufficiently quickly for risk-mitigation actions to be implemented at each examined site if an EEW alarm is triggered. Greater than 99% average accuracy is achieved when 2.4 s of warning time are still available at the nearest site (SJ; 10 km triggered station radius) and when 4.6 s are still available at the middle site (PA; 30 km triggered station radius), which would both enable a safe place to be found a few steps away (see Table 4). Predicted optimal decisions are 100% accurate at the SF site when 10.1 s of warning time are still available (50 km triggered station radius), allowing a safe place to be found in the same room (from Table 4). These lead times justify the case-study assumptions made.
about consequences mitigated (i.e., non-collapse casualties and laptop breakages avoided) when an EEW alert is triggered. Potential warning times could be used as additional inputs to the methodology to ensure that data provided on consequences mitigated for given actions is reasonable, using information from the final column of Table 4; however further discussion on this topic is left to future work.

4 | CONCLUSIONS

This study has developed a novel methodology for risk-informed EEW that uniquely combines multi-criteria decisional and earthquake-engineering-related tools, for informed stakeholder-driven decision making. In particular, the proposed methodology can be used to select the optimal risk-mitigation action for current seismic hazard conditions, accounting for stakeholder priorities toward multiple types of uncertain consequences that do not need to be measured in monetary terms.

The proposed methodology was applied to EEW in a hypothetical Californian school, considering the traditional performance metrics (consequences) assessed in PBEE and a range of stakeholder preferences toward them. This application clearly demonstrated that the optimal risk-management action for a given level of impending shaking can depend on stakeholder priorities. For example (based on completely assumptive data), it was found that the school’s EEW system would trigger at a site in Palo Alto approximately once every 10 years if stakeholders placed higher importance on limiting casualties, whereas it would only trigger approximately half as frequently if stakeholders prioritized the mitigation of downtime. This finding emphasizes the importance of considering end-user preferences in short-term earthquake risk management, which should be accounted for in future installations of EEW.

Furthermore, it was shown that the methodology can be used to make decisions as a function of (1) magnitude–distance pairs, as well as (2) seismic station/early signal data that act as input to EEW algorithms for estimating source parameters. Decision making based on (2) is particularly useful as it is more representative of realistic scenarios (where information on the incoming event is uncertain) and the required EEW algorithm data can be precomputed offline ahead of the event for efficient real-time risk management. For three different sites of the hypothetical school, three scenario events and one source location, it was found that the proportion of correct EEW decisions based on (2) increases with the density of stations triggered (as expected) and high accuracy is reached sufficiently quickly for risk-mitigation actions to be implemented, underlining the credibility of the proposed methodology.

Future work will explicitly treat potential warning times as an input of the methodology, to guide the selection of appropriate and feasible case-specific risk-management actions in further applications.

The results of this study represent a significant advancement over state-of-the-art risk-based decision-making methods for EEW that mainly rely on cost–benefit analyses. The developed algorithm could be packaged as a software plug-in to existing operational EEW platforms, transforming these systems into powerful end-user-driven tools that effectively promote and prioritize seismic resilience.

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AUTHOR CONTRIBUTIONS

Both authors helped to conceive and design the research. G.C. drafted the written content of the manuscript, which C.G. also reviewed. G.C. performed the calculations. Both authors developed the figures.

CONFLICT OF INTEREST

There are no conflicts of interest associated with this research.

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**APPENDIX A: ALGORITHM**

Algorithm 1 contains the decision-making algorithm proposed in this paper. All variables are as defined in Section 2.

**ALGORITHM 1**

**Step 1: Mod_PBEE**

1.1: Determine $f(\mathbf{im}|\mathbf{d})$, based on the relevant EEW algorithm.

1.2: Use the result of Step 1.1 and required structural modeling information (see Appendix C) to generate $E^\mathbf{A}(C^\mathbf{i}_{j}|\mathbf{d})$, based on the PBEE algorithm framework provided in Equation (1).

1.3: Calculate $p(FA|\mathbf{d})$ according to Equation (4).

1.4: Use the results of Steps 1.2 and 1.3, as well as stakeholder-reported values of $\psi_{ij}$ and $\alpha_j(\mathbf{d})$, to calculate $E^\mathbf{A}(C^\mathbf{i}_{j}|\mathbf{d}) = p(FA|\mathbf{d})e^{\psi_{ji}} + \alpha_j(\mathbf{d})E^\mathbf{A}(C^\mathbf{i}_{j}|\mathbf{d})$.

1.5: Repeat Step 1.4 for all $N_a$ actions and $N_c$ consequence criteria, to develop the consequence matrix.

**Step 2: Mod_MCDM**

2.1: Use the results of Step 1.5 to generate $r_{A_i,C_j}$ according to Equation (6).

2.2: Use stakeholder-reported values of $w_j$ to calculate $r_{A_i,C_j}|w_j$.

2.3: Repeat Steps 2.1 and 2.2 for all $N_a$ actions and $A_i$, and $N_c$ consequence criteria, to develop the decision matrix.

**Step 3: Mod_Decision**

3.1: Use the results of Step 2.3 to calculate $v^+_j = min(r_{A_i,C_j},w_j)$ and $v^-_j = max(r_{A_i,C_j},w_j)$.

3.2: Use the results of Steps 2.3 and 3.1, and Equations (7)-(9), to determine the optimal action.

**APPENDIX B: DERIVING EQUATION (17)**

Using Equation (14) and accounting for the assumptions that $P_d$ measurements are lognormally distributed as well as independent, the likelihood function for these measurements across $N_s$ stations can be expressed as:

\[
f \left( P_{d1}, P_{d2}, ..., P_{dN_s} | m \right) = \left( \frac{1}{\sqrt{2\pi} \sigma_{\ln(P_d)}} \right)^{N_s} \prod_{k=1}^{N_s} \left( \frac{1}{P_{d_k}} \right) e^{-\frac{1}{2} \left( \frac{\ln(P_{dk}) - \ln(P_d)}{\sigma_{\ln(P_d)}} \right)^2} e^{-\frac{1}{2} \left( \frac{\ln(P_{dk})^2 - \ln(P_d)^2}{\sigma_{\ln(P_d)}^2} \right)}
\]

By (1) substituting Equations (B.1) and (12) into Equation (11); and (2) canceling the $\left( \frac{1}{\sqrt{2\pi} \sigma_{\ln(P_d)}} \right)^{N_s}$, $(\prod_{k=1}^{N_s} \frac{1}{P_{dk}} e^{-\beta m})$, and $(e^{-\beta M_{\min}} - e^{-\beta M_{\max}})$ terms that are common to the numerator and the denominator, the expression for $f(m|\mathbf{d})$ becomes:

\[
f(m|\mathbf{d}) = \frac{\sum_{k=1}^{N_s} \left( 2\ln(P_{dk})^2 - \ln(P_{dk}) \right)^2}{2\sigma_{\ln(P_d)}^2} e^{-\beta m} \frac{\sum_{k=1}^{N_s} \ln(P_{dk})}{2\ln(P_d)} e^{-\beta M_{\max}} d\mathbf{m}
\]

Substituting Equation (15) for $\mu_{\ln(P_d)}$ reduces Equation (B.2) to (17) for:

\[
x(\mathbf{d}) = x_1 \left[ 2md_1 - 2(x_2d_3 + x_3d_4) - N_sx_1m^2 \right] + 2x_1m(x_2d_3 + N_sx_3) - \left( x_1 \left( x_2^2d_4 + 2x_2x_3d_2 + N_sx_3^2 \right) \right)
\]

where $d_3 = \sum_{k=1}^{N_s} \ln(P_{dk})\log_{10}(r_k)$, $d_4 = \sum_{k=1}^{N_s} \log_{10}(r_k^2)$, and all other variables are as defined previously. Finally, canceling nonmagnitude-dependent terms (since they are common to both the numerator and the denominator of Equation 17) simplifies Equation (B.3) to (18).

**APPENDIX C: STRUCTURAL MODELING DETAILS**

Structural modeling details are provided in Table C.1.
### Table C.1: Structural modeling details of the hypothetical school, including FEMA P-58 parameters. Note that the FEMA P-58 analyses were run using the SP3 software (https://www.hbrisk.com/)

| Parameter                  | Value                          | Additional notes/Justification                                                                                                                                 |
|----------------------------|--------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Year of construction       | 2003                           |                                                                                                                                                               |
| Occupancy                  | Elementary school              | Corresponds with typical characteristics of suburban U.S. schools (FEMA, 2010; The National Institute of Building Sciences, 2010)                                |
| Number of stories          | 2                              |                                                                                                                                                               |
| Lateral system             | Reinforced concrete space moment frame |                                                                                                                                                           |
| Length in direction 1 (m)  | 26                             | Corresponds with plan layout of precast concrete school modeled in O’Reilly et al. (2018)                                                                     |
| Length in direction 2 (m)  | 42                             |                                                                                                                                                               |
| Story height (m)           | 4                              |                                                                                                                                                               |
| Fundamental period ($T_1$) | 0.4                            | FEMA (2013) assumed value for building                                                                                                                        |
| Yield base shear coefficient ($V'_y$) | 0.1663 g                      | SP3 default input values to the FEMA P-58 simplified analysis procedure (detailed in Section 5.3 of FEMA (2018)) for building, $a$ and $\alpha$ are used in the lateral displacement equations of Miranda (1999), to compute the $\Delta_i$ variable of the simplified methodology according to eqs. 5–10 of FEMA (2018). |
| Yield story drift ratio ($\Delta_y$) | 0.0075                     |                                                                                                                                                               |
| First mode mass ratio      | 1                              |                                                                                                                                                               |
| $\alpha$                   | 0.01                           |                                                                                                                                                               |
| $\alpha$                   | 12.5                           |                                                                                                                                                               |
| Soil site class            | D                              | Corresponds with assumed $V_s30$ values at each site                                                                                                          |
| Collapse capacity          | Lognormally distributed with 10% probability of collapse for hazard level with 2% probability of exceedance in 50 years and dispersion = 0.6 | Assumed model, in line with previous studies for buildings of similar age and identical lateral system (e.g., Haselton & Deierlein, 2007); FEMA P-58 default value for collapse dispersion. Hazard levels are computed at each site using the 2018 US National Seismic Hazard Model (Petersen et al., 2020) |
| FEMA P-58 structural components | ACI 318 concrete SMF (B1041.002a & B1041.002b) | SP3 default components for building, except UD. UD has user-defined cost and repair time consequence distributions, which are set as follows: cost is normally distributed with mean = $500 and standard deviation = 0.05; repair time is normally distributed with mean = 0.1 day and standard deviation = 0.05. |
| FEMA P-58 nonstructural components | Wall partition, metal stud (C1011.001a); HVAC ducting (D3041.011c); curtain walls (B2022.002); suspended ceiling (C3032.003a, C3032.003b, C3032.003c, & C3032.003d); independent pendant lighting (C3034.002); concrete stairs with seismic joints (C2011.011a); desktop electronics including computers, monitors, stereos, etc. on a slip resistant surface (UD) |                                                                 |
| FEMA P-58 component quantities | 10 UD per floor; all other quantities are P-58 median values for building layout |                                                                 |
| Building population model  | FEMA P-58 default model for occupancy |                                                                                                           |
| Building replacement cost  | 270                            | SP3 default value for building                                                                                                                                     |
| Building replacement time  | 169                            | SP3 default value for building                                                                                                                                     |
| Building repair time type  | Serial                         |                                                                                                                                  |