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An Earthquake Early Warning Decision Support System for Railway Bridge Infrastructure

Ekin Ozer
Assistant Professor, School of Civil Engineering, University College Dublin, Dublin, Ireland

Formerly Research Associate, Dept. of Civil and Environmental Engineering, University of Strathclyde, Glasgow, UK

Gemma Cremen
Lecturer, Dept. of Civil, Environmental and Geomatic Engineering, University College London, London, UK

Carmine Galasso
Professor, Dept. of Civil, Environmental and Geomatic Engineering, University College London, London, UK

Pierre Gehl
Research Engineer, Risks and Prevention Decision, Bureau de Recherches Géologiques et Minières (BRGM), Orléans, France

Enrico Tubaldi
Senior Lecturer, Dept. of Civil and Environmental Engineering, University of Strathclyde, Glasgow, UK

ABSTRACT: Earthquake early warning (EEW) systems deliver actionable information seconds before the arrival of damaging seismic waves from an oncoming earthquake at a target site. Such information can potentially contribute to mitigating the negative impacts of earthquakes on the operation of infrastructure assets. EEW-related decision making should use risk-based protocols, and the evaluation of the benefits of EEW systems should address all the possible rupture scenarios that may affect a specific location (or asset). This paper addresses these requirements for EEW on railway bridge structures. We first develop a risk-informed EEW decision support system (DSS) for these assets, combining information on site-specific seismic hazard, time-dependent EEW algorithm outputs, probabilistic seismic demand modeling, damage and derailment fragilities, and seismic loss models. These components are integrated into a multi-criteria decision-making framework that accounts for diverse stakeholder perspectives on risk. We then propose an approach for quantifying the loss-mitigation benefits (i.e., effectiveness) of the EEW-DSS across all possible relevant rupture scenarios affecting a railway bridge, based on value of information theory and accounting for dynamic accuracy/lead-time trade-offs related to EEW performance. A multi-span reinforced concrete railway bridge in Northeastern Spain is adopted as a testbed to showcase the proposed EEW-DSS and investigate its benefits. The findings from the analysis shed light on the importance of risk-based, uncertainty-informed, and stakeholder-oriented decision making to the loss-mitigation effectiveness of EEW for a railway bridge.

1. INTRODUCTION

Earthquake early warning (EEW) systems and algorithms estimate the arrival of (damaging) earthquake-induced ground motions at a site with seconds to tens of seconds of advance notice. The information provided by EEW can trigger various rapid actions depending on the target audience and assets to be protected. Examples of these actions include i) “drop, cover, and hold on” maneuvers by the public, preventing injuries (e.g., Wu and Kanamori 2008); ii) automated shutdown of gas supplies, avoiding fire following earthquake events; iii) slowing down trains, mitigating derailments (e.g., Strauss and Allen, 2016). EEW can be configured to different hardware and software architectures and classified as either regional (Zuccolo et al., 2021), on-site (Colombelli et al., 2015), or hybrid (Iervolino et al., 2006) systems. For a comprehensive review of the recent state-of-the-art in operational EEW systems worldwide, interested readers are referred to Cremen and Galasso (2020).

EEW systems traditionally trigger alarms (and associated loss-mitigation actions) based on hazard-level information (Allen and Kanamori, 2003). Such an approach excludes important knowledge pertaining to the seismic behavior of the built environment. To maximize the practical effectiveness of EEW, there is a need to unify the seismological computations of EEW systems (as well as the related uncertainties) with corresponding risk-based engineering-driven consequence predictions for infrastructure (e.g., Cremen et al., 2021a). To further facilitate well-informed decision making for EEW, these predictions should be integrated into a multi-criteria decision analysis approach that accounts for diverse stakeholder preferences towards different types of consequences that might occur (Le Guenan et al., 2016; Cremen and Galasso, 2021b).

The effectiveness of EEW systems is a relatively well explored topic in the literature, and is a critical issue given the uncertainties that exist at each stage in the underlying calculations (e.g., Minson et al., 2018, Wald, 2020, Cremen et al., 2021c). Most investigations of EEW effectiveness have centered on their ability to estimate accurate/timely seismological or hazard-related parameters for single earthquake scenarios (e.g., Minson et al., 2017, Zuccolo et al., 2021). However, to provide insight into the long-term benefits of EEW for a specific infrastructure asset or urban system of interest, it is necessary to focus on the risk-based consequences associated with all possible relevant rupture scenarios that might affect them. The concept of value of information (VoI; Howard, 1966) can be leveraged to address this requirement (Cheng et al., 2014).

The VoI concept is based on the average value a stakeholder is willing to pay for more information to improve their decision making. VoI began to play an important part in civil infrastructure decision making with the pioneering works of Pozzi & Der Kiureghian (2011) and Thons & Faber (2013) on the VoI of structural health monitoring. An extensive review of VoI applications in civil engineering can be found in Zhang et al. (2021). In the context of EEW, VoI may be interpreted as the cost savings from the loss-mitigation measures triggered by the information from the EEW system.

This study focuses on developing and assessing the effectiveness of a risk-based EEW decision-making approach (i.e., decision support system, DSS) for railway bridges, which have been largely overlooked in previous EEW studies. The potential benefits of EEW for this type of infrastructure is an important consideration, given the interconnected consequences that can result from their earthquake-induced damage, including train derailment and wider transportation network disruption and resulting socio-economic consequences. The proposed EEW DSS is based on the engineering-oriented multi-criteria decision-making approach to EEW introduced in Cremen and Galasso (2021). The VoI concept is then leveraged to investigate the benefits of the EEW-DSS in mitigating earthquake-related railway bridge losses (both direct and cascading).

2. METHODOLOGY

This section presents the proposed EEW DSS and an approach to assess its effectiveness for a single railway bridge. Note that only an outline description of the methodology is provided in this paper (e.g., equations are omitted) due to space constraints. A more detailed account of the procedure is provided elsewhere by the authors (Ozer et al., 2023).

2.1. EEW DSS

The proposed EEW DSS comprises five main calculation components, outlined in the following subsections (see also Figure 1). In general terms, the methodology consists of a performance-based earthquake early warning procedure for estimating real-time EEW-related losses at the bridge (induced by train derailment). The procedure is integrated within a multi-criteria decision-making framework to account for diverse stakeholder priorities on seismic risk.

2.1.1. Step 1: Real-time Probabilistic Seismic Hazard Analysis (RTPSHA)

The first step of the methodology is a real-time adaptation of Cornell's (1968) probabilistic seismic hazard analysis formulation, following the approach proposed by Iervolino et al. (2006). Based on time-dependent seismic network measurements and associated early warning parameters (collectively denoted as $\boldsymbol{d}$), probabilistic estimates of the incoming earthquake's magnitude and source-to-site distance can be determined in real time. Appropriate ground-motion models (GMMs) can then be used to translate these uncertain source parameter estimates into a time-dependent distribution of site-specific ground-shaking intensities associated with the incoming event $f(im|\boldsymbol{d})$. The exact intensity measures adopted depend on the probabilistic seismic demand model to be developed (details to follow).

2.1.2. Step 2: Probabilistic Seismic Demand Modeling

The relationship between the ground-motion intensity measure output from the RTPSHA process and engineering demand parameters (EDPs) for the railway bridge $f(\boldsymbol{edp}|im)$ is established through cloud analysis (Bazurro et al., 1998). The EDPs included in the model depend on how derailment is defined (details to follow).

2.1.3. Step 3: Derailment Analysis

Train derailment is interpreted in terms of EDPs exceeding designated thresholds. Three modes of train derailment on the bridge are considered: i) derailment due to transient vibratory motions of the bridge; ii) derailment due to permanent deformations on the bridge caused by structural damage; and iii) derailment due to collapse of the bridge. Fragility curves are developed to quantify the probability of the *x*th mode of derailment for the ground-shaking intensity measure output from the RTPSHA $p(D_x|im)$, using Monte Carlo simulations to first determine the probability of derailment occurrence as a function of EDPs.

2.1.4. Step 4: Consequence Modeling

This component of the methodology computes the real-time expected consequences associated with implementing (A) or not ($\bar{A}$) an EEW-triggered slow-down of trains approaching the railway bridge for an incoming earthquake $E(C_j^A|\boldsymbol{d})$, leveraging the derailment fragilities developed as well as time-dependent information on train locations, speed, deceleration ability, and the amount of EEW lead time available. Only derailment-related consequences are considered in this study; consequences associated with structural damage (e.g., repair cost) are ignored in this case, given that they cannot be reduced through EEW. The examined consequences are expressed in the form of downtime hours and casualties.

2.1.5. Step 5:Multi-Criteria Decision-Making

This component of the methodology accounts for stakeholders' preferences (w_j) towards each type of consequence examined as well as the time-dependent expected magnitude of each consequence $E\left(C_j^A\middle|\boldsymbol{d}\right)$, to determine the real-time optimal decision to take (A_{opt}, i.e., trigger or not a slow-down of trains). The Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS; Yoon and Hwang, 1995) is used for decision evaluation, in line with Cremen and Galasso (2021). This approach deems the best decision to be the one that optimizes a trade-off between the best and worst outcomes (where each outcome corresponds to a consequence weighted in line with stakeholder preferences).

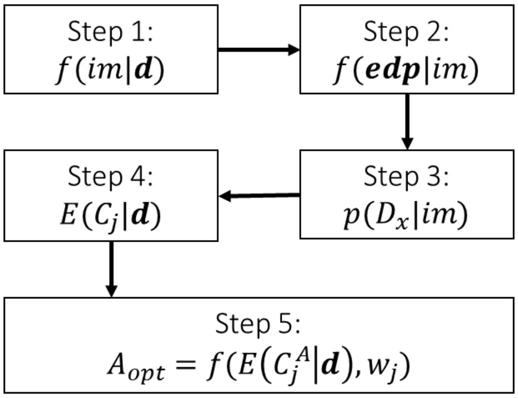

Figure 1: Workflow of the proposed EEW DSS.

2.2. Value of Information Assessment Framework

The concept of VoI assesses the beneficial contributions of the EEW-DSS in terms of minimizing the stakeholder-weighted consequences. Two time-dependent VoI metrics are proposed to express i) the value of taking the optimal action determined by the EEW-DSS relative to the case of having no information and taking no action; ii) the value of taking the optimal action based on the imperfect (uncertain) information provided by the EEW system relative to the ideal case of taking the optimal action based on perfect magnitude and source-to-site distance information for the incoming event. These metrics are quantified for all possible earthquake scenarios affecting the railway bridge (above a minimum magnitude threshold), and the final assessment of EEW effectiveness is based on the average values of each metric.

3. CASE-STUDY APPLICATION

This section demonstrates the development and evaluation of an EEW-DSS for Mugo Viaducto del Rio, a testbed multi-span railway bridge in Northeastern Spain (see Figure 2). The reinforced/prestressed concrete bridge consists of a total span of approximately 700 m and rests on 11 bridge piers that are assumed to consist of rectangular hollow sections. Characteristic bridge features are retrieved from Manterola Armisen et al. (2008).

The bridge is located in a seismically active zone, and the surrounding region is instrumented with a network of seismometers (see Figure 3). One thousand stochastic earthquake scenarios are generated by sampling events from the seven seismogenic sources surrounding the bridge, using corresponding Gutenberg-Richter distribution parameters from the Seismic Hazard Harmonization in Europe (SHARE) project's area source model (Giardini et al. 2013; Woessner et al., 2013). In this case, the intensity measure of interest is the spectral displacement at the fundamental period of the bridge (1.03 s). Five hundred ground-shaking intensity values for each event are sampled at the bridge's location, using the Akkar et al. (2014) GMM for Europe. These values correspond to the "perfect information" case discussed in Section 2.2.

3.1. Steps 1 to 3

RTPSHA is simulated for each event, using a dynamic degree of information ($\boldsymbol{d}$) available in real-time from between $n=1$ and $n=34$ triggered seismic stations located near the site, according to the following procedure: (1) Determine the real-time magnitude probability distribution from the Allen and Kanamori (2003) EEW magnitude-scaling relationship in combination with the Bayesian formulation proposed by Iervolino et al. (2009), and neglect EEW-related location estimation uncertainty; and (2) Sample five hundred ground-shaking intensity estimates from the Akkar et al. (2014) GMM and the magnitude distribution obtained in (1).

A nonlinear finite element model is developed for the bridge using OpenSees. The probabilistic seismic demand model is generated based on the ground motion dataset used in Tubaldi et al. (2022). The model expresses the relationship between acceleration and transient displacement EDPs and the geometric mean of spectral displacement at the bridge's fundamental period Sd_{geom}. Derailment fragility curves are finally expressed in terms of the spectral displacement intensity measure. More details on Steps 1 to 3 are omitted for brevity but can be found in Ozer et al. (2023).

Figure 2: Multi-span railway bridge in Spain.

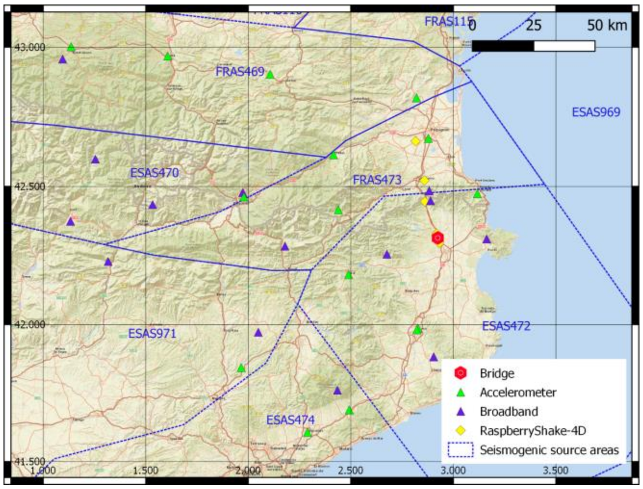

Figure 3: Location of the testbed bridge and the surrounding seismic network.

3.2. *Steps 4 to 5*

Expected casualty (*I: Individuals*) and downtime (*H: Hours)* consequences are computed for each earthquake event, in the case of triggering an EEW-related slow-down of trains or not, given $\boldsymbol{d}$ from n stations. These consequences are also calculated for both possible actions assuming perfect information on the incoming event's magnitude (M^*) and source-to-site distance (R^*). Figure 4 provides example expected values, *E(I)* and *E(H)*, for a relatively large earthquake event scenario ($M^* = 6.7, R^* = 57\ km$). Assumptions on train-related parameters and other information related to the consequence calculations are detailed in Ozer et al. (2023).

It can be seen in Figure 4 that the expected consequences vary according to the number of stations triggered and, therefore, the underlying accuracy of the magnitude distribution, as anticipated. As n increases: (1) the expected consequences dependent on EEW information $\boldsymbol{d}$ become closer to the true values dependent on M^* and R^*, due to greater accuracy in the EEW-related magnitude distribution; and (2) the expected consequences for A increase, as the decreasing lead-time available diminishes the loss-mitigation effects of triggering a slow-down. Various hypothetical stakeholder preferences towards casualties and downtime (w_j) are investigated for the final multi-criteria decision-making step, using the combination of weights provided in Table 1. These weights reflect a gradual transition from casualty-dominated (Case 1) to downtime-dominated (Case 4) risk perspectives.

Figure 5 presents the optimal decision for each combination of weights and all rupture scenarios examined, based on the expected consequences calculated according to $\boldsymbol{d}$ at the time when one station is triggered and those calculated with perfect information $\{M^*, R^*\}$. The results are expressed in terms of $E(Sd_{geom}|M^*,R^*)$, the mean value of the spectral displacement intensity measure according to perfect information.

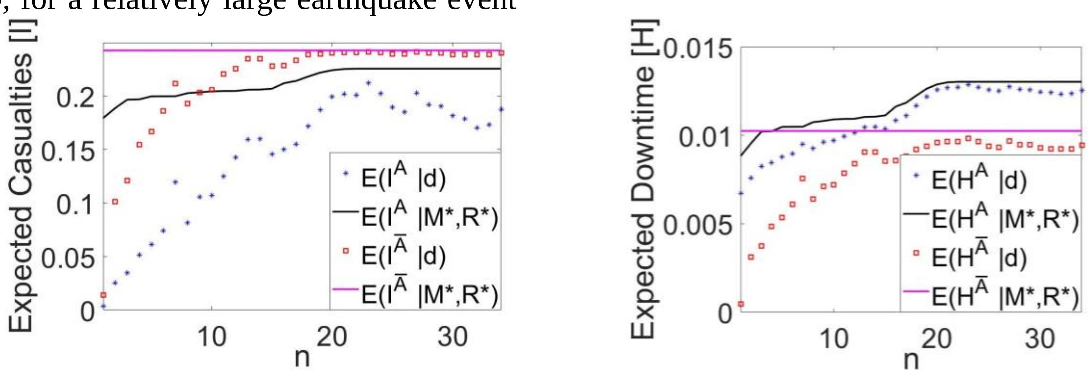

Figure 4: Expected consequences for an example earthquake scenario, n: no of stations. All variables are the same as previously defined. For instance,, $E\left(I^{\bar{A}}\middle|\boldsymbol{d}\right)$ *denotes the expected casualties if no action is taken, conditional on real-time information available for the earthquake.*

It is seen in Figure 5 that the optimal decision is always to take action if only casualties are considered important to mitigate (Case 1). Perspectives that place positive varying emphasis on downtime (Cases 2 to 4) result in an optimal decision of taking no action for ***d***, but for some scenarios would result in the opposite optimal decision if perfect information on the incoming earthquakes was known.

Table 1. Hypothetical stakeholder w_j values investigated.

Criteria	Stakeholder cases			
	1	2	3	4
Casualty	1.	0.67	0.33	0.
Downtime	0.	0.33	0.67	1.

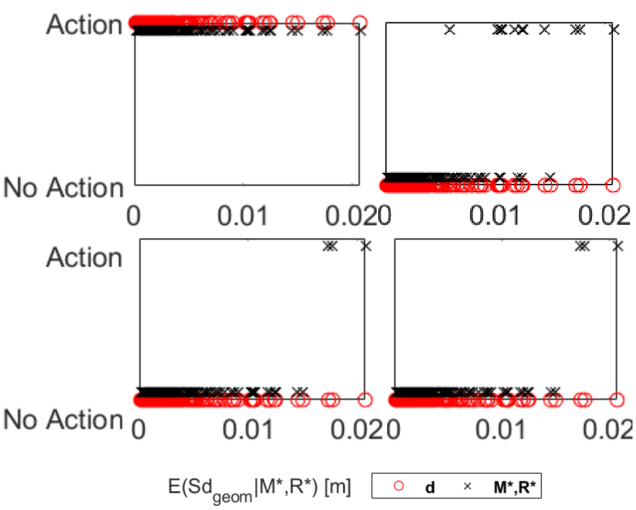

Figure 5: Action (trigger a slow-down of the train) vs no action decisions for different stakeholder risk preferences (Upper row: Case 1-2, Lower row: Case 3-4).

Table 2 presents example results of the first VoI assessment metric, assuming *n=8* for the EEW system and using the stakeholder preference cases previously introduced. When only casualties are considered (Case 1) or prioritized over downtime (Case 2), the optimal action is often to trigger the EEW-related slow-down of trains, which: (1) mitigates casualties relative to having no system, providing a positive expected VoI for *I*; but (2) creates unnecessary downtime, leading to a negative expected VoI for *H*. The optimal action (given ***d***) is not to trigger EEW for Case 3 and Case 4, so there is no expected value of information associated with having the EEW-DSS in these cases.

Table 2. Expected VoI of the proposed EEW-DSS relative to not having it.

Criteria	Value of information per each case			
	1	2	3	4
Casualty	0.3201	0.0911	0.	0.
Downtime	-2.6327	-0.0048	0.	0.

Table 3 presents example results of the second VoI assessment metric, using *n=8* for the EEW system and the stakeholder preference cases previously introduced. The results show that there is no gain from perfect early warning estimations if only casualties are considered (Case 1), since the optimal decision for both perfect and imperfect information is to trigger the EEW system in this case. The VoI provided by perfect early warning information in the other cases is due to deviations in the optimal decisions produced. Since the optimal decision tends towards taking no action as higher priority is placed on mitigating downtime, regardless of the level of information available, the expected value of information for *H* is minimal. The expected VoI for *I* in Cases 3 and 4 underline the benefits of avoiding missed alarms with perfect information. Note that more detailed findings of this study can be found in Ozer et al. (2023).

Table 3. Expected VoI of an EEW-DSS based on perfect information relative to the imperfect one.

Criteria	Value of information per each case			
	1	2	3	4
Casualty	0.	0.0477	0.1090	0.0823
Downtime	0.	0.0028	0.0002	0.0005

4. CONCLUSIONS

In this paper an EEW-DSS for mitigating seismic risk at railway bridges wass developed and its benefits were assessed. The paper leveraged an engineering-oriented approach to creating the EEW-DSS and integrated multi-criteria decision-making theory to account for varying stakeholder priorities towards different types of seismic risk. The benefits of the proposed EEW-DSS were quantified in terms of bespoke VoI metrics that accounted for the risk preferences input to the multi-criteria decision-making component, as well as all possible earthquake scenarios that may affect bridge-related decisions. Key findings are:

- Optimal decisions produced by the EEW-DSS depend on stakeholder prioritization of different consequence types, as well as the accuracy of the underlying source-parameter estimates and the lead time available for risk-reduction efforts.
- The number of triggered stations used in the EEW-DSS has competing effects on its effectiveness. Increasingly accurate source-parameter predictions yielded by larger amounts of recording station data result in more accurate optimal decisions but also decrease the effectiveness of EEW due to the amplified risks of train derailment as lead time shortens. The overall effectiveness of the EEW-DSS depends on a combination of these two factors.
- Findings of the case study indicate that there can be no (or even negative) expected VoI from an EEW-DSS system for minimizing downtime consequences. This is because no action is often the optimal decision for the low ground-shaking values that dominate the seismic hazard of the case-study area, for which issuing an EEW alarm would only unnecessarily trigger a disruptive bridge inspection.
- The benefits of having perfect source-parameter information in the EEW-DSS can depend on the risk priorities of stakeholders. The case study's findings imply that stakeholders who only care about minimizing casualties would experience little to no marginal benefits in having a perfect EEW-DSS, since the more uncertain loss estimates obtained with the raw EEW parameters still lead to the correct optimal decision (i.e., trigger the alarm). On the other hand, stakeholders that heavily prioritize the minimization of downtime losses do benefit from using perfect information since, in particular, it can eliminate some missed alarm opportunities associated with the more uncertain source-parameter estimates.

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