A decision-making approach for operational earthquake forecasting

Authors details:

Alireza Azarbakht[1,*] https://orcid.org/0000-0003-3627-652X, Email: alireza.azarbakht@strath.ac.uk

Archie Rudman[1] Email: archie.rudman@strath.ac.uk

John Douglas[1] https://orcid.org/0000-0003-3822-0060, Email: john.douglas@strath.ac.uk

[1]University of Strathclyde
Department of Civil and Environmental Engineering
James Weir Building
75 Montrose Street
Glasgow
G1 1XJ
United Kingdom

* Corresponding author: Alireza Azarbakht, Email: alireza.azarbakht@strath.ac.uk

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Keywords

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Abstract

Decision making to mitigate the effects of natural hazards, such as earthquakes, has always been a challenging subject. This is particularly the case in periods of increased seismicity (e.g. in a foreshock or aftershock period of a major earthquake) when the population is anxious and would like advice but when the chance of potentially damaging earthquake ground motions in the coming days remains low. In this study, a decision-making method based on multiple criteria is combined with cost-benefit analyses to create a hybrid decision-making framework to help decide amongst potential loss mitigation actions (or even to take no action). The proposed framework is demonstrated for three hypothetical case studies using Patras (Greece) as an example of a high seismicity location. The results show that the proposed approach is flexible enough to adapt to new problems, end-users and stakeholders. Additionally, it is revealed that reasonable mitigation actions are viable and financially beneficial during periods of increased seismic hazard in order to reduce the potential consequences of earthquakes. Finally, the case studies show that the results can be highly sensitive to the inputs to the framework and hence it is vital to involve end users to help constrain these inputs when making such calculations.

1. Introduction

A disaster is a social situation characterised by non-routine, life-threatening physical destruction (Quarantelli 1998). Disasters can be classified as: natural, for those caused by geophysical, hydrological, meteorological, biological, extra-terrestrial, or climatological hazards; anthropogenic (technological); or technological triggered by a natural disaster (Natech) (Guha-Sapir et al. 2016). Until recently, droughts and floods killed most people worldwide, but deaths from these events are now generally low. The deadliest disasters today (apart from disease pandemics) tend to be triggered by earthquakes (e.g. Haiti 2010, Tohoku 2011) (Ritchie 2014).

Disaster/emergency management is the body of policy and administrative decisions, the operational activities, the actors, and technologies that pertain to the various stages and levels of a disaster (Lettieri et al. 2009). Due to the immense losses caused by natural hazards, effective disaster management is vital. Because of the changing nature of disasters and the uncertainty in managing them, disaster management is studied across many disciplines. Disaster management involves strategic interactions among various decision-makers, including different levels of government, private companies and non-profit organisations, making Operational Earthquake Forecasting (OEF) an exciting approach in this field (Goltz 2015). OEF is an emerging concept that aims to provide short-term forecasts of earthquakes to increase alertness and readiness among decision-makers and to initiate civil protection actions (Jordan et al. 2011; Field and Milner 2018).

Procedures for short-term forecasts through time-dependent seismic hazard assessment have been applied in various studies over the past decade, particularly in periods of increased seismicity such as following a large earthquake (Convertito and Zollo 2011; Peruzza et al. 2017). Despite acknowledged weaknesses (Jordan et al. 2011; Wang 2015; Wang and Rogers 2014), OEF is the best available approach to forecast future earthquakes. The short-term probability of a severe earthquake is low (often less than one per cent daily) even in a heightened hazard situation, which presents a formidable challenge when making decisions based on OEF (Woo and Marzocchi 2014). Therefore, no comprehensive framework for OEF decision-making is yet available in the technical literature, although using cost-benefit analyses has been proposed (e.g. Douglas and Azarbakht, 2021). The purpose of this article is to propose another approach for decision making in the context of OEF and to apply the approach in some hypothetical situations.

Decisions to undertake mitigation actions based on OEF depend on the balance between costs and benefits, which are specific to the risk at hand (Field et al. 2016). Because these decisions are contingent on a host of economic, political, and psychological considerations that lie beyond the science of hazard analysis, scientific information about future earthquake activity should be developed independently of any specific risk assessment or mitigation effort (Field et al. 2016). Moreover, all validated OEF information should be made available to all potential end-users in an appropriate well-formatted and timely manner. These hazard-risk separation and transparency principles imply that seismologists should provide potential end-users with complete, probabilistic forecasts, including their epistemic uncertainties (Jordan et al. 2014). The OEF systems should be policy-neutral. In other words, OEF systems should not withhold information until some activity level or probability threshold is exceeded, or until a "significant" mainshock has occurred. Otherwise, doing so would not only imply that we know how to define these things for all potential users, but would also effectively put scientists in the inappropriate role of making policy decisions (Field et al. 2016). In summary, OEF systems should be used to inform potential decision-makers at all levels, not as a holistic decision-making tool itself.

Recent events have revealed the public's hunger during ongoing earthquake sequences for information from OEF. It is well known that information vacuums invite unfounded predictions and misinformation (Mileti and Peek 2000), such as the rumours on Twitter that "experts are holding back on a prediction to avoid panic" within hours of the 2010 El Mayor–Cucapah earthquake (Jordan and Jones 2010). The level of apparent certainty provided by amateur predictors can also be particularly attractive and therefore distracting (Marzocchi 2012). The infamous L'Aquila trial, in which seven Italian officials were charged with involuntary manslaughter, was at least partly a consequence of miscommunications about earthquake risk by the Italian Department of Civil Protection (Field et al. 2016). That agency convened its Grand Risk Commission before the L'Aquila earthquake to address ill-founded earthquake predictions that were worrying the public during the seismic sequence preceding the L'Aquila mainshock. Still, this Commission lacked the operational capabilities to accurately assess and report on the evolving seismic hazard (Marzocchi 2012). The best solution in such predicaments is to have an OEF system that produces authoritative scientific information (Jordan 2013; Jordan et al. 2011).

The probability from a time-dependent forecast, produced by short-term forecasting models, can be quite high (Probability Gains, PG>100) relative to the time-independent probability (e.g. Gulia et al., 2016). In these situations, the forecasting intervals are typically much shorter than the recurrence intervals of large earthquakes (days compared to hundreds of years), and the probability of potentially damaging earthquakes remains much less than unity (generally <1% per day). As a result, although the value of long-term forecasts for ensuring seismic safety is clear, the interpretation of short-term forecasts is problematic, because earthquake probabilities may vary over many orders of magnitude. Such forecasts cannot provide earthquake "predictions" associated with high probabilities. Translating such low-probability forecasts into effective decision-making is a difficult challenge. Therefore, it is necessary to establish earthquake probability thresholds for different mitigation actions by means of, for example, a cost-benefit analysis (Douglas and Azarbakht 2021; Azarbakht et al. 2020) and also by taking psychological preparedness and resilience into account. In this context, a multi-criteria decision support system (DSS) is also helpful since cost-benefit analyses are only straightforward when one action is compared to the case of no action, and such analyses cannot account for end-user priorities that are not expressed in financial terms. Alert procedures should be standardised to facilitate decisions at different levels of government and among the public if necessary. Moreover, the principles of effective public communication established by social science research should be applied to delivering seismic hazard information (Jordan et al., 2011).

In the present study, we adapt a recent multi-criteria DSS, initially introduced by Cremen and Galasso (2021) for Earthquake Early Warning (EEW) systems, for use in an OEF framework. The method is described in detail in the following section. This method is then applied to three case studies and some conclusions drawn.

2. Method

As mentioned in the previous section, decision making in OEF is still a challenging area of research since many considerations influence this problem, and the likelihood of false alarms is always high. Multi-criteria decision making using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was initially proposed in general terms by Hwang and Yoon (1981) and implemented in the field of earthquake engineering by Caterino et al. (2008). Cremen and Galasso (2021) have recently adapted this framework to EEW. However, EEW only considers two possible actions (trigger or not trigger an alarm), whereas many mitigation actions could be triggered by OEF. It is also worth emphasising that OEF concerns a longer time frame (often days or weeks) instead of a few seconds in the case of EEW. In EEW, it is considered almost certain that an earthquake will occur in the next few seconds (probability near to unity), whereas for OEF, the chance of an earthquake actually occurring during the forecast period (e.g. next days or next week) is small, which means the risk of a ”false alarm” is much higher, making it more likely that the best action is “no action”. Actions will generally be far reaching and have a more significant impact in the context of OEF than for EEW as they will be in place for a long time and affect many people. Nevertheless, significant planning for low probability/high consequence events (such as earthquakes) may be made without being overly disruptive to social and economic activities. This is because many actions triggered by OEF are actions that are routinely performed. Actions such as drills and exercises, communicating on recommended evacuation routes in case of tsunamis and having a survival kit can be reinforced during periods of enhanced seismic hazard since public concern about a possible event in the short term is increased.

Being inspired by the approach of Cremen and Galasso (2021), the method of the current study starts with defining a set of OEF mitigation actions ({A_i}) that have been selected by the end user, and also the option of taking no action ($\bar{A}$). We also need to assign a specific consequence ({C_j}) to each action. Each consequence is case-specific and associated with a group of corresponding uncertain consequences if a particular action is taken. A given weight ({w_i}) can be assigned to each consequence criterion to reflect its importance and to comply with end-user preferences. The explicit incorporation of these preferences results in improvements over conventional decision-making approaches. The suggested action(s) can be subject to further scrutiny using a cost-benefit analysis. Therefore, we have combined TOPSIS with a cost-benefit analysis to construct a comprehensive framework for an OEF DSS.

The main steps in the proposed OEF DSS framework are described below. The first step aims at defining the probabilistic consequences ({C_j}) for each action ({A_i}), as seen in Table 1. The main consequences are assumed to be direct cost, downtime and casualties, as these have been widely used in the field of earthquake engineering. Nevertheless, other consequences could be added to this framework, e.g. indirect costs, reputation loss and environmental damage.

Table 1. The consequence matrix in the proposed OEF DSS algorithm.

	C_1, direct cost ($)	C_2, downtime (days)	C_3, casualties (number)
A_1	Expected A_1 action direct and reconditioning costs + expected direct cost from estimated shaking that is not eliminated with mitigation action A_1 = E(A1,C1)	Expected A_1 action downtime + expected downtime from estimated shaking that is not eliminated with mitigation action A_1 = E(A1,C2)	Expected A_1 action casualties + expected casualties from estimated shaking that is not eliminated with mitigation action A_1 = E(A1,C3)
. . .	. . .	. . .	. . .
A_{N_a}	Expected A_{N_a} action direct and reconditioning costs + expected direct cost from estimated shaking that is not eliminated with mitigation action A_{N_a} = E(A_{N_a},C1)	Expected A_{N_a} action downtime + expected downtime from estimated shaking that is not eliminated with mitigation action A_{N_a} = E(A_{N_a},C2)	Expected A_{N_a} action casualties + expected casualties from estimated shaking that is not eliminated with mitigation action A_{N_a} = E(A_{N_a},C3)
$\bar{A}$ (no action)	Expected direct cost from estimated shaking if no action is taken = E($\bar{A}$,C1)	Expected downtime from estimated shaking if no action is taken = E($\bar{A}$,C2)	Expected casualties from estimated shaking if no action is taken = E($\bar{A}$,C3)

We also need to assume a crisis period, which usually is during a foreshock or aftershock sequence where seismicity increases significantly. It is worth mentioning that OEF mitigation actions need to be undertaken for a relatively long period of time (e.g. weeks or months) and cannot be altered daily (or hourly) as this would create confusion in the population. Also, there needs to be some simplification in order for the calculations to be feasible as it is not possible to assess exactly how the seismic hazard will change in the future. Hence, we assume a 30 days' time duration for the crisis period, to appropriately simulate a heightened hazard situation prior to a possible mainshock. Therefore, we assume that we have access to the results of a time-dependent probabilistic seismic hazard analysis, i.e. an estimated daily frequency of exceedance (λ_{IM}) of a given Intensity Measure (IM). λ_{IM} is usually represented versus the value of an IM, e.g. peak ground acceleration (PGA) or response spectral acceleration for a given structural period and a given critical damping ratio.

Next, we need to define an IM threshold based on the end user's preferences, e.g. if falling secondary systems (such as air conditions or unanchored furniture) are of interest, one may choose a PGA threshold equal to 0.05g, roughly corresponding to macroseismic intensity V (Caprio et al. 2015), to define the initiation of damage to such systems. A fragility function can be defined based on the estimate of the median threshold and commonly assumed log-normal distribution (or, in fact, another appropriate distribution) with a particular standard deviation expressing the uncertainty in damage initiation. It is worth emphasising that one can use an actual (analytical or experimental) fragility function for a given structure under investigation but here we are considering generic systems.

In the following, P represents the cumulative distribution function for the fragility curve, and $P(\mathrm{C}|\mathrm{im})$ denotes the probability of damage at a given IM. Therefore, we can calculate the mean daily frequency of damage (λ_d), using Equation 1 [for more details, see, for example, Gkimprixis et al. (2019) and Azarbakht et al. (2015)].

$$\lambda_d = \int_0^\infty P(\mathrm{C}|\mathrm{im})|d\lambda_{IM}(im)| \tag{1}$$

Then the mean daily frequency of damage (λ_d) can be transformed into the mean probability of damage during the crisis period ('cp' days, we assume cp=30 days in the current study) by assuming a Poisson distribution. With p_{cp} we can calculate the consequences of the no-action case and account for the associated uncertainty. In other words, all the consequences will be multiplied by p_{cp} in the case of taking no-action. Then, we need to normalise and weight, based on the importance of each category, the results. For this, we use Equation (2) to normalise the consequence matrix (see Table 2) (Hwang and Yoon 1981; Cremen and Galasso 2021):

$$r_{A_i,C_j} = \frac{\mathrm{E}(A_i, C_j)}{\sqrt{\sum_{k=1}^{N_a}[\mathrm{E}(A_k, C_j)^2] + \mathrm{E}(\bar{A}, C_j)^2]}} \tag{2}$$

where r_{A_i,C_j} is the normalised value of the j[th] criterion for the i[th] action (the rest of the parameters were defined previously). r_{A_i,C_j} values are then weighted, ideally based on end-user preferences for each criterion, to create the decision matrix seen in Table 2. One option is to use the analytical hierarchy process of Saaty (1980) to obtain the weightings ($\{w_i\}$). This framework involves an end-user doing a series of pairwise comparisons for each criterion, on the basis of qualitative phrasing to determine their relative importance.

Table 2. The decision matrix in the proposed OEF DSS algorithm.

	C_1, direct cost ($)	C_2, downtime (days)	C_3, casualties (number)
A_1	$r_{A_1,C_1} \times w_1$	$r_{A_1,C_2} \times w_2$	$r_{A_1,C_3} \times w_3$
.	.	.	.
.	.	.	.
.	.	.	.
A_{N_a}	$r_{A_{N_a},C_1} \times w_1$	$r_{A_{N_a},C_2} \times w_2$	$r_{A_{N_a},C_3} \times w_3$
$\bar{A}$ (no action)	$r_{\bar{A},C_1} \times w_1$	$r_{\bar{A},C_2} \times w_2$	$r_{\bar{A},C_3} \times w_3$

Finally, we need to determine the optimal decision among $\{A_i\}$ and $\bar{A}$. For this, we need to find the maximum and minimum values for each criterion among all possible options. As all the criteria in this study are negative consequences, the best quantity of the j[th] criterion (v_j^+) is its minimum value, which is, $v_j^+ = \min_j(r_{A_1,C_j \times w_j}, \dots, r_{A_{N_a},C_j \times w_j}, r_{\bar{A},C_j \times w_j})$ and the worst value (v_j^-) is its maximum value, which is, $v_j^- = \max_j(r_{A_1,C_j \times w_j}, \dots, r_{A_{N_a},C_j \times w_j}, r_{\bar{A},C_j \times w_j})$. The total distance of a given action, A_i, from the best (y_i^+) and worst (y_i^-) solutions are then, respectively, calculated as:

$$y_i^+ = \sqrt{\sum_{j=1}^{N_c}(v_j^+ - (r_{A_i,C_j} \times w_j))^2} \tag{3}$$

$$y_i^- = \sqrt{\sum_{j=1}^{N_c} (v_j^- - (r_{A_i,C_j} \times w_j))^2} \qquad (4)$$

Consequently, the optimal action is the largest S_i value, which is calculated as:

$$S_i = \frac{y_i^-}{y_i^+ + y_i^-} \qquad (5)$$

The final output is the 'Closeness Value' (S_i, known as C hereafter), i.e. the similarity to the best possible solution. This could be used in future applications to determine which OEF mitigation actions are recommended, as the longer time frame for OEF compared with EEW allows for more thorough decision making. This method is demonstrated below for three different hypothetical examples but the method can be applied to help guide other decisions in the context of OEF.

3. Case study 1: DSS for boxes falling in a warehouse

As seen in Figure 1, boxes falling in a warehouse have been observed in many past earthquakes (FEMA E-74, 2012). Therefore, a hypothetical example of a warehouse holding stock on shelves, located in Patras (Greece) is investigated in this section. This city is chosen since it is in one of Europe's highest seismicity regions and it is a testbed of the TURNkey project[1]. Time-dependent seismic hazard analysis for this region is discussed in Azarbakht et al. (2021). However, for simplicity, the long-term (time-independent) seismic hazard in this study is taken from the European Seismic Hazard Model 2013 (ESHM13) (Woessner et al. 2015), and different scenarios of heightened seismic hazard are assumed to form a generic study. Each scenario is the product of a constant PG and the hazard curve from ESHM13 for Patras as written in Equation (6).

$$\lambda_{IM}(im) = PG.\lambda'_{IM}(im) \qquad (6)$$

where $\lambda'_{IM}(im)$ is the non-heightened daily frequency of exceedance of a given IM, which corresponds to long-term (background) hazard conditions, and $\lambda_{IM}(im)$ is the heightened daily frequency of exceedance of a given IM, which was also used in Equation (1), PGs equal to 1, 10, 100 and 1000 are assumed to cover the range of potential values (e.g. Douglas and Azarbakht, 2021).

Table 3. The adapted consequence matrix for the warehouse example (case study 1).

	Direct cost ($)	Downtime (hours)	Number injured

[1] Towards more Earthquake-resilient Urban Societies through a Multi-sensor-based Information System enabling Earthquake Forecasting, Early Warning and Rapid Response actions (https://earthquake-turnkey.eu/)

Move Boxes to Floor	Quantity of stock × Hours to move stock × Hourly wage of workers	λ_d × Downtime duration in hours	0
Secure Boxes to Shelves	Quantity of stock × (Equipment cost + Hours to secure stock × Hourly wage of worker)	λ_d × Downtime duration in hours	0
Move Boxes to Storage	Hourly wage of worker × (Transport time + Quantity of stock × Hours to move stock) + Storage cost	λ_d × (Quantity of stock × Hours to move stock + transport time)	0
No OEF Action	λ_d× Value of stock	λ_d × Replacement time	λ_d× Number of workers

Table 4. Input parameters for the warehouse example (case study 1).

Type of parameter	**Value**
Number of items in warehouse	100
Value of one item of stock	$100/item
Number of employees at risk within warehouse	10
Wage of employee	$20/hour
Cost of renting a storage facility for a month	$250/month
Cost of equipment to secure stock to shelves per stock	$10/stock
Time to replace entire stock if damaged	5 days
Time to move one item from shelf to floor	0.1 hrs
Time to secure one item on a shelf	0.2 hrs
Time to transport entire stock to storage	0.333 hrs
Downtime cost per day	$1,000/day
Cost per injury	$10,000/injury
Weightings of each criterion, [W_{direct_cost}, $W_{downtime}$, W_{injury}]	[1/3 1/3 1/3]

Four possible OEF actions are assessed on the basis of three criteria consisting of: direct cost, downtime, and injuries as illustrated in Table 1 and Table 3. It is also assumed that with no OEF in place, all staff at risk would be injured and all stock would be damaged (if an earthquake occurred), that it would take five days for the stock to be replaced, and that the cost of replacing the stock would be the same as the value of the original stock. In contrast, it is assumed that with OEF in place, there would be no injuries to staff and no stock would be damaged and, hence, the stock would not require replacement. It is worth emphasising that the damage only occurs if the earthquake actually happens. If there is no OEF in place, but there is no earthquake, then the warehouse is undamaged. The criteria are reliant on ”the probability of a false alarm”, or, in other words, the probability that the earthquake shaking will not exceed the PGA threshold during the crisis period. This ”false alarm” would trigger downtime, which is not beneficial to the warehouse. The input parameters for this case study are summarised in Table . It should be noted that these values would be fixed based on discussions with the end user and tailored to the actual warehouse and stock in a real application of the DSS.

Figure 1. Damage to overloaded racks during the 1994 Northridge (USA) earthquake (FEMA 460, 2005)

Originally a step function was assumed: i.e. below a PGA threshold nothing falls or is damaged and above the threshold everything falls. Such a step function was used by Douglas and Azarbakht (2021) for their Europe-wide cost-benefit analyses for OEF. As shown in Figure 2(left), such a function led to a rapid decrease in actions becoming viable, with the curves for each potential action quickly plateauing. Incorporating the convolution of the fragility and hazard functions accounts for uncertainty in the damage threshold, which is more realistic. It is worth mentioning that element-specific fragility curves would ideally be used here to account for the element's characteristics in terms of height, size, shape and so forth. For comparison, the results for the step function and the fragility function are shown in Figure 2. For the purpose of simplicity, we have assumed a log-normal fragility curve with the logarithmic mean identical to the PGA threshold and a logarithmic standard deviation equal to 0.84, based on the global intensity-PGA conversion formula of Caprio et al. (2015).

As can be seen in Figure 2 (PG=100), plotting C for a range of PGA thresholds shows that moving the boxes to storage is consistently the best option. The lowest threshold of 0.05g is ranked at 0.995 (i.e. very close to the optimum of 1), meaning that it is the best-case scenario – lowest cost, downtime, and injuries out of the four options. However, increasing the PGA threshold makes all of the mitigation actions less viable, and the option of taking no action becomes more acceptable. This is because the chances of the earthquake shaking exceeding the PGA threshold becomes smaller, so actions become less beneficial as they rely on the earthquake occurring to be cost and time effective.

It is important to note that moving the boxes to storage for small PGA thresholds is still the best course to take. This is due to the assumption that if the earthquake occurred with no mitigation in place, it would damage all the stock and injure everyone working there, which is not necessarily true for an earthquake causing such a low PGA, considering that λ_d is highest for the lowest PGA thresholds.

As TOPSIS only compares the available options, ranking them from best to worst, it does not consider whether the superior action is financially justifiable (Hwang and Yoon 1981). In other words, an action may be considered the best out of the set of actions considered, but it may still not be the most beneficial amongst all possible actions or beneficial at all. Thanks to the longer time frame available to consider mitigation actions for OEF, it is possible to introduce a secondary check to the DSS, by considering cost-benefit analyses, to address this limitation of TOPSIS.

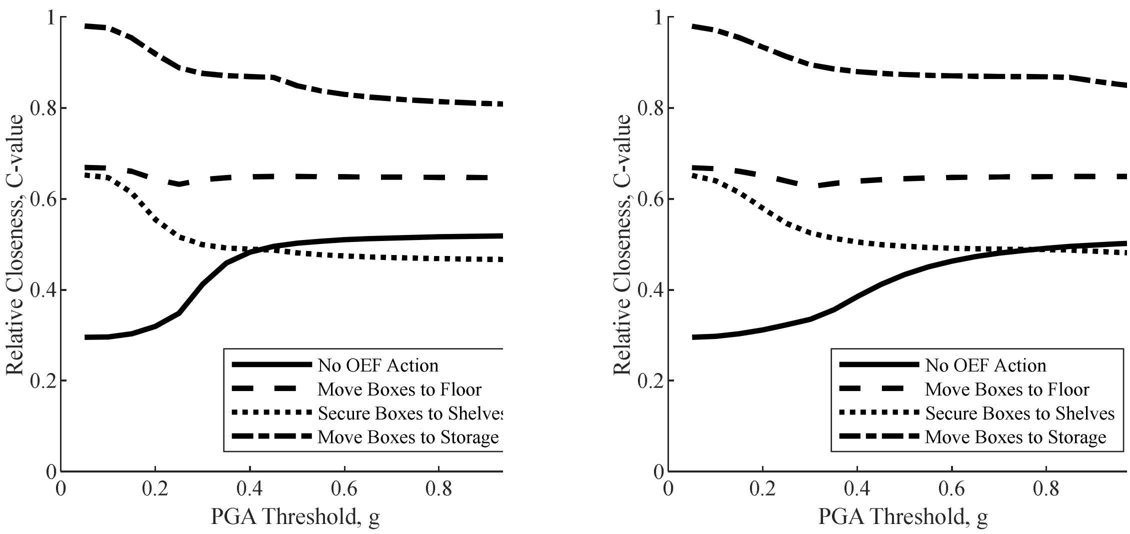


Figure 2. (left): C versus different PGA thresholds using a step function, (right): C versus different PGA thresholds using a log-normal fragility function. PG=100.

By manipulating the consequence matrix from the DSS algorithm, by summing each criterion multiplied by costs, i.e. a downtime cost of \$1,000(/day) and an injury cost of \$10,000(/injury), as shown in Table , it is possible to calculate the total cost and the mitigated loss corresponding to each action within a cost-benefit analysis using these equations:

$$\text{Cost of } \{A_{N_a}\} \text{ action } = \mathrm{E}(A_{N_a}, \mathrm{C1}) \tag{7}$$

$$\text{Mitigated loss by } \{A_{N_a}\} \text{ action } = [\mathrm{E}(\bar{A}, \mathrm{C1}) + \mathrm{E}(\bar{A}, \mathrm{C2}) \times \text{Downtime\_cost(/person)} + \mathrm{E}(\bar{A}, \mathrm{C3}) \times \text{Injury\_cost(/person)}] - \mathrm{E}(A_{N_a}, \mathrm{C2}) \times \text{Downtime\_cost(/person)} - \mathrm{E}(A_{N_a}, \mathrm{C3}) \times \text{Injury\_cost(/person)} \tag{8}$$

The costs, Equation (7), obtained from Table 1 and Table 3, can then be compared to the mitigated loss, Equation (8), by calculating the benefit-to-cost ratio, R, expressed by (Marzocchi and Woo, 2009; Woo, 2010; Douglas and Azarbakht, 2021):

$$R = \frac{p_{cp} \times \text{Mitigated loss by } \{A_{N_a}\} \text{ action}}{\text{Cost of } \{A_{N_a}\} \text{ action}} \tag{9}$$

for each of the OEF mitigation actions. In the case of PG equal to 10 (seismic hazard increased to ten times the background level), the right graph in Figure 3 shows R versus PGA threshold, where an action is assumed cost-beneficial when the corresponding R is greater than unity (benefits are greater than the costs). It is worth mentioning that this analysis does not consider the no-action case, only mitigation actions. On the other hand, TOPSIS compares all the actions, including the no-action case; however, it does not explicitly compute the financial benefits of each action.

As can be seen in Figure 3, the TOPSIS algorithm recommends ”Moving boxes to storage” as the superior action for all PGA thresholds and with a remarkable distance from the other actions. However, this action is not the best financially, as seen in the right-hand graph of Figure 3, but still the benefit-to-cost ratio is greater than unity. The ”Moving boxes to storage” is apparently more costly when compared to the other actions; however, it minimises the downtime by more than the other actions. Therefore, TOPSIS helps decide based on the consequence matrix elements, and further being normalized in the decision matrix to be unitless, and looks at different actions to find the action that is closest to the optimum solution. This means that ”Moving boxes to storage” has a more balanced benefit in the consequence matrix compared to the other actions. On the other hand, R only considers monetary values and looks at different actions individually. The cost of “Moving boxes to storage“ is almost 2.5 times the “Moving boxes to floor“ cost. Their implications in terms of downtime is the opposite, however. The risk of injuries is zero for both actions. This is why ”Moving boxes to storage” is not optimum in terms of R. Therefore, we suggest neglecting the TOPSIS results if the benefit-to-cost ratio is less than unity. In other words, we add the cost-benefit analysis on top of the TOPSIS algorithm to confirm that the action recommended by the TOPSIS algorithm is individually financially justifiable. Additionally, the benefit-to-cost ratio expresses the level of financial benefits, as shown in Figure 4.

The final results of the DSS are shown in Figure 4, where the top line presents the results of the TOPSIS-only algorithm. The other lines present the results of combining TOPSIS and cost-benefit analysis. The classification is based on R, with “Highly cost-beneficial”, “Clearly cost-beneficial”, “Moderately cost-beneficial”, “Marginally cost-beneficial”, and “Not cost-beneficial” defined by $R \geq 5$, $2.5 \leq R < 5$, $1.5 \leq R < 2.5$, $1 \leq R < 1.5$ and $R < 1$, respectively (Douglas and Azarbakht 2021). As seen in Figure 4, TOPSIS recommends the ”Moving boxes to storage” action for all PGA thresholds but R reveals that this action is highly cost-beneficial up to 0.2g, clearly cost-beneficial between 0.25g and 0.35g, moderately cost-beneficial between 0.4g and 0.45g, marginally cost-beneficial between 0.5g and 0.55g, and not cost-beneficial beyond 0.6g.

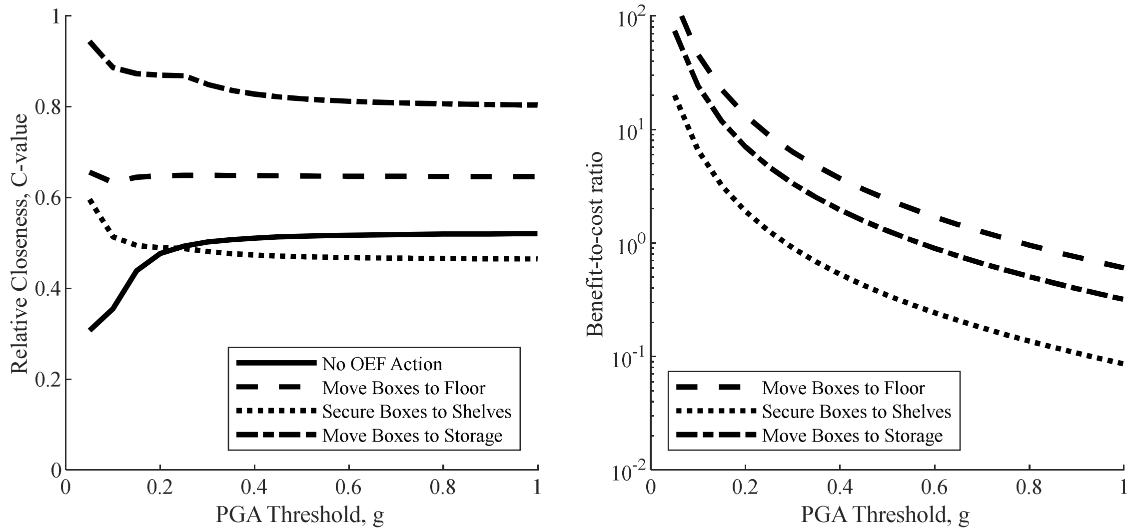


Figure 3. (left): C versus different PGA thresholds, (right): R versus PGA thresholds for different OEF actions. PG=10.

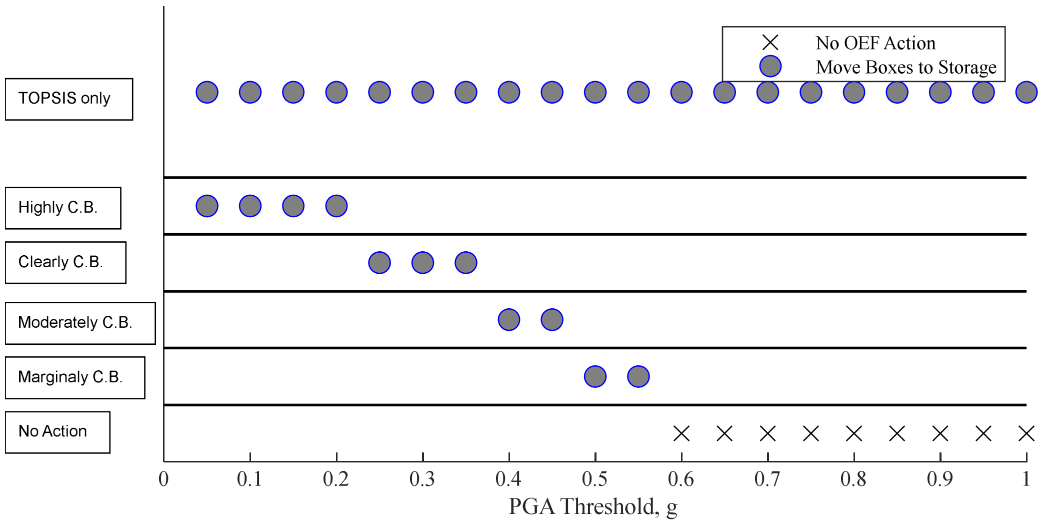
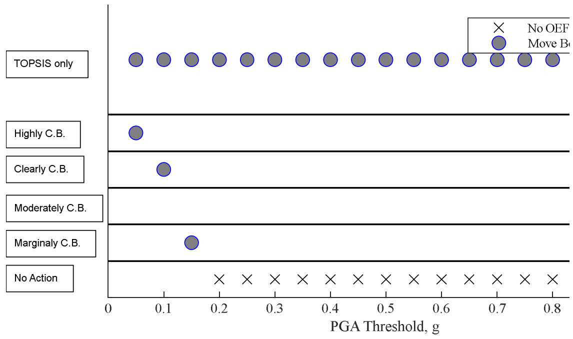
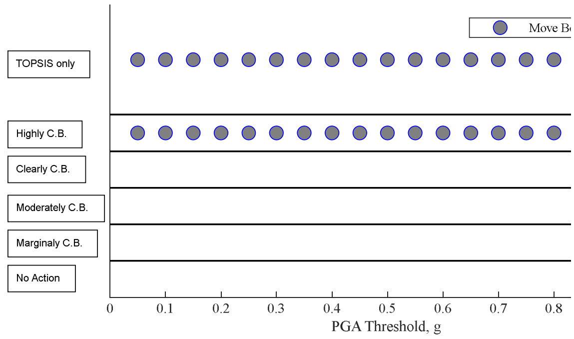


Figure 4. The final recommended actions for TOPSIS only (top row), and the combination of TOPSIS and cost-benefit analyses. PG=10.

We have assumed PG=10 and equal weighting for different consequences, i.e. direct costs, downtime, and injuries in Figures 3 and 4. Results for other PG values are shown in Figure 5, confirming that no OEF action is financially justifiable in the normal hazard situation (PG=1) for PGA thresholds greater than 0.15g. In other words, this confirms that risk mitigation is recommended even in the normal hazard situation if minor earthquake shaking (PGA thresholds less than 0.15g) can cause stock to fall from the warehouse shelves. However, TOPSIS recommends ”Moving boxes to storage” at any level of heightened hazard, without considering its financial trade-off.

As seen in the top right graph of Figure 5, the recommended action is highly cost-beneficial for PG=100 in the case of a PGA threshold less than 0.8g, and this is true for the entire considered PGA range in the case of PG equal to 1,000 (bottom graph). In addition, the recommended OEF action is cost-beneficial even in the case of a PGA threshold equal to 1g when PG=1,000, which is obviously a period of extremely high seismic hazard.





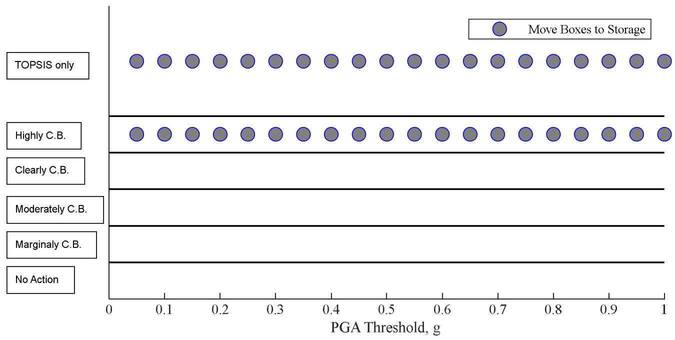


Figure 5. The final recommended actions for different scenarios of heightened seismic hazard, as represented by PG equal to 1 (top-left), 100 (top-right), and 1,000 (bottom).

The last question to investigate in this section is the impact of a specific end user wanting to put more emphasis on a particular criterion in the consequence matrix. The results of the decision making for three different weighting combinations are shown in Figure 6. To emphasis a specific criterion the weight corresponding to this criterion is set equal to 1/2 and giving 1/4 weight to the two other criteria (as opposed to a weight of 1/3 for all three). As seen in Figure 6, the recommended mitigation action is the same ("Moving boxes to storage"); however, no action becomes more beneficial when the emphasis is on the direct cost or the downtime, but when the emphasis is on the injury criterion "No action" is never recommended, at least for the mitigation actions considered in this study. These conclusions hold for PG equal to 1, 100, and 1,000.

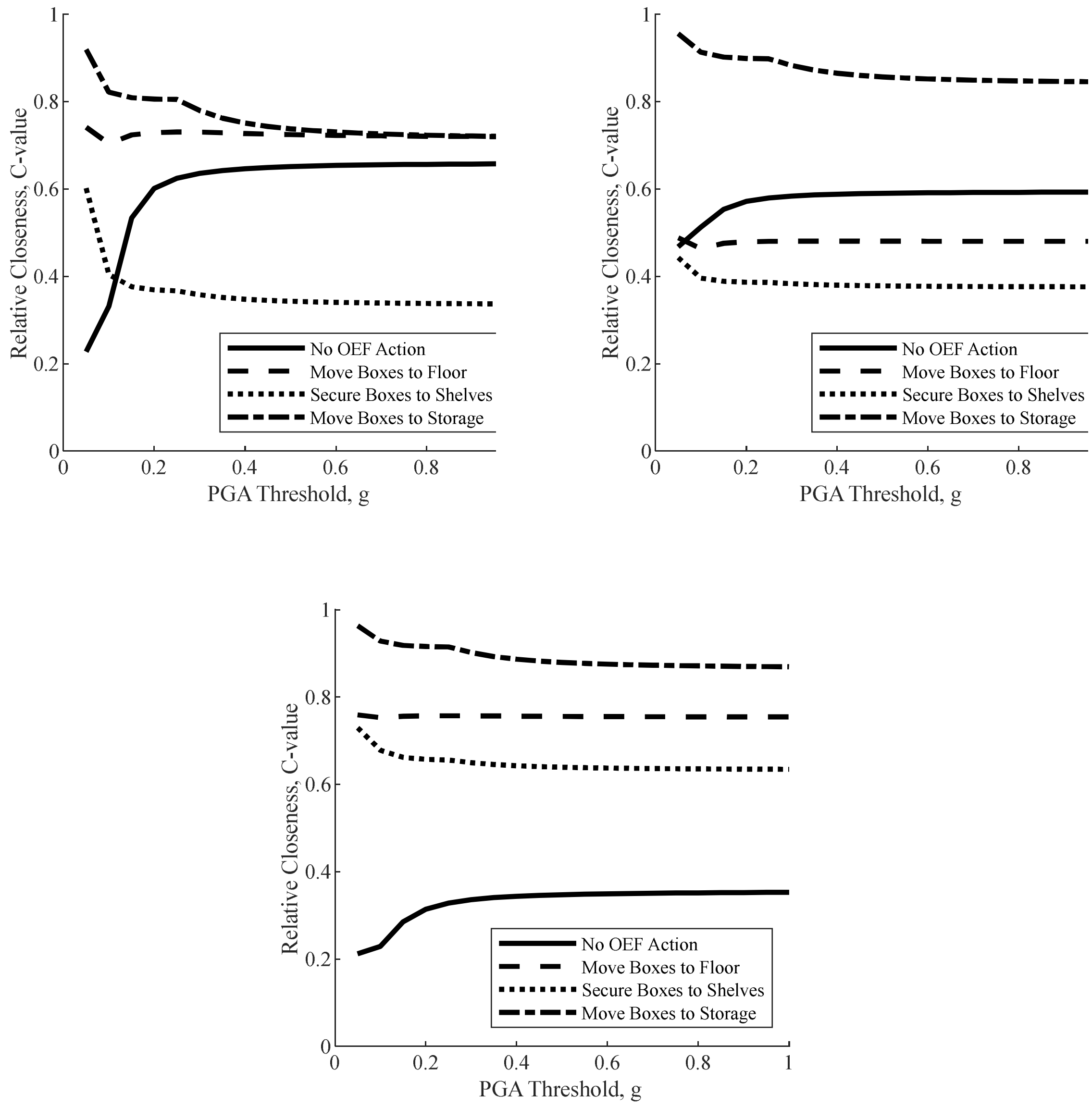


Figure 6. C for weights emphasising the direct cost (top-left), downtime (top-right), and injuries (bottom).

4. Case study 2: DSS for secondary systems falling from a building

It is essential to implement the DSS algorithm for different examples to check whether the method has general applicability and whether it can be easily adapted to different end users. It is not efficient to need different methods for different industries and end users. In this section an example considering the risk of a secondary system (such as a sign, air conditioning unit, façade or road blocking due to a wall damage) falling from a building, and potentially hitting a pedestrian or causing damage to the immediate area, is considered (Figure 7 shows an example of this situation in a US earthquake). This case study is based on the same hazard curve for Patras and uses the same three criteria: direct costs, downtime, and injuries, as in the previous example.

It is assumed that the secondary system will fall if no OEF mitigation action is taken and that it will injure someone if it does fall. Additionally, if the system were to fall, it would be damaged and require five days to be replaced. The absence of the element will lead to a 50% reduction in productivity and revenue for the business. On the other hand, with the OEF action taken, the system will not fall or be damaged, and there will be no injuries. If the building is evacuated, it will take half a working day (four hours) for it to be considered safe to return. On the basis of these assumptions, the adapted consequence matrix and all the input variables are, respectively, summarised in Table and Table 6.

Table 5. The adapted consequence matrix for the secondary systems falling from a building example (case study 2).

	Direct cost ($)	Downtime (hours)	Number injured
Remove element	Hours to remove element × Hourly wage of employee + Storage cost × Duration of crisis + Productivity reduction × Revenue × Duration of crisis	λ_d × (Hours to remove element + Productivity reduction × Duration of crisis)	0
Secure element	Hours to secure element × Hourly wage of employee + Equipment cost	λ_d × Hours to secure element	0
No OEF Action	λ_d × (Cost of element + Cost of damage + Productivity reduction × Revenue × Replacement time)	λ_d × (Replacement time + Closure time if an earthquake occurs)	λ_d × Number of employees

Figure 7. Failure of a commercial sign in the 1979 Imperial Valley, California earthquake (FEMA E-74, 2012).

Table 6. Input parameters for the example of a secondary systems falling from a building.

Type of parameter	**Value**
Cost of element	$200
Cost of damage	$200/item

Revenue per day	$500/day
Productivity reduction	0.5
Cost of renting a storage facility	$300/month
Cost of equipment to secure element	$10/element
Number of employees at risk	5
Wage of employee	$20/hour
Time to remove element	1 hour
Time to secure element	2 hrs
Time to shut if an earthquake occurs	4 hrs
Time to replace an element	5 days
Downtime cost per day	$1,000/day
Cost per injury	$10,000/injury
Weightings of each criterion, [W_{direct_cost}, $W_{downtime}$, W_{injury}]	[1/3 1/3 1/3]

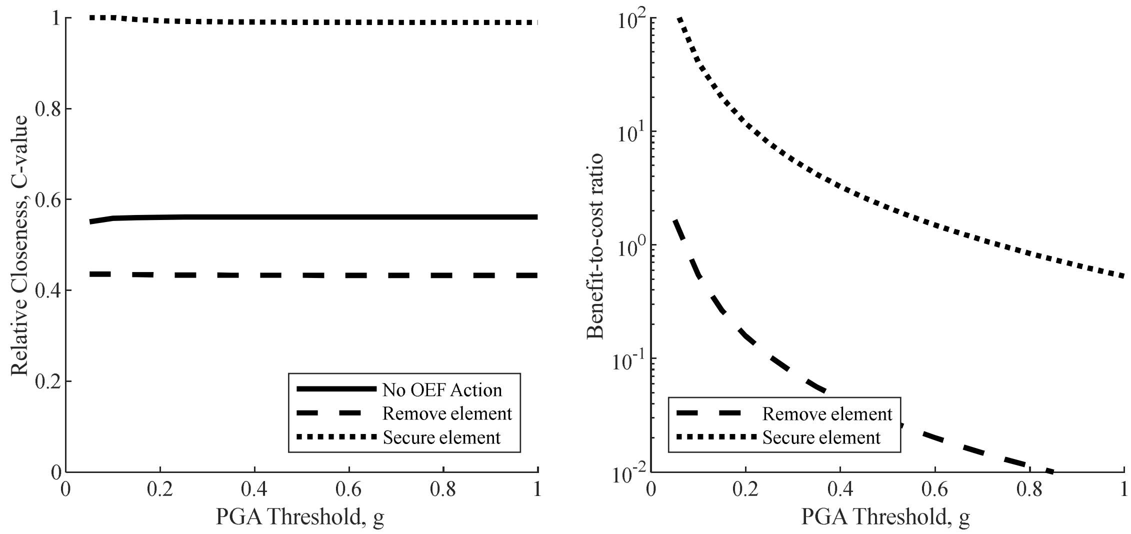


Figure 8. (left): C versus different PGA thresholds, (right): R versus PGA thresholds for different OEF actions for the example of a secondary systems falling from a building.

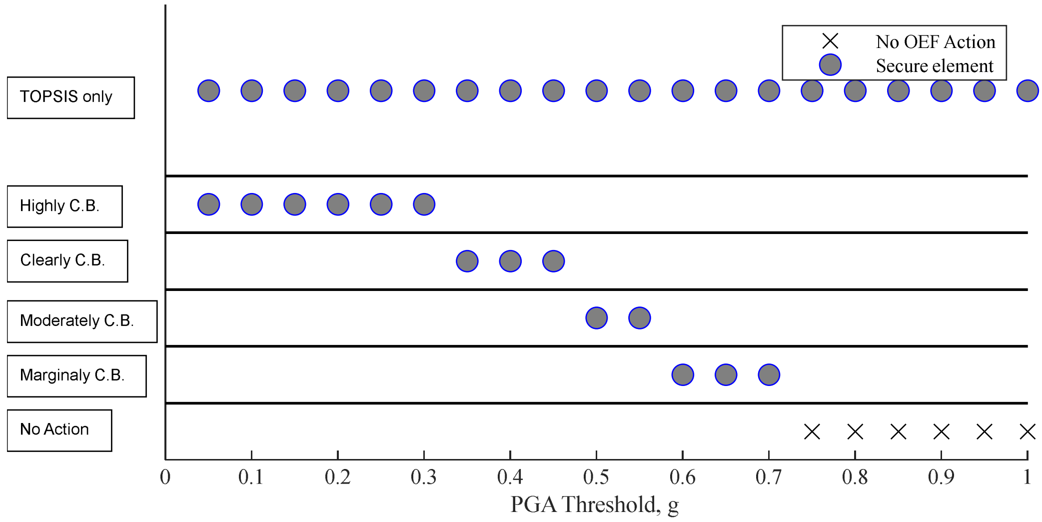


Figure 9. The final result of the TOPSIS only algorithm (top row), and the combination of TOPSIS and cost-benefit analyses for the example of a secondary system falling from a building.

The results are shown in Figure 8 and Figure 9 in the case of PG equal to 10 and the equal weighting scheme. The example of a secondary system falling from a building contrasts greatly with the previous example of boxes falling in a warehouse. Here there are three well-defined and separated optimal actions, with few trade-offs within the rankings – an outcome that was not necessarily expected. The present example was harder to conceptualise, and it would help greatly to contact relevant end-users to help refine the consequence matrix. Considering this example greatly benefits the refinement of the DSS as it shows how different situations can be considered. The C values change slightly at small PGA threshold values; however, they begin to plateau at 0.2g and reach constant values around 1g. In fact, at higher PGA values, the plateau of the curve is reached as the probability of exceeding the threshold becomes low enough that it can be considered zero, with the probability of the threshold not being exceeded obviously being very close to one. Due to the nature of OEF, which operates in the domain of (very) small probabilities, it would be interesting to explore further the idea of creating general graphs for different DSS examples using the probability of exceeding the PGA threshold as zero and understanding how well defined the action rankings are. This could be done in the pre-crisis period, when there are many different actions to consider, thereby allowing the weaker actions (i.e. those with less mitigation potential) to be weeded out and a more efficient determination of the best mitigation action to be made.

As seen in Figure 8, ”No action” is better than ”Removing element” because this action does not solve the inherent problem and it also results in a significant reduction in business productivity (this conclusion holds for all considered PG values). On the other hand, the ”Securing element” action is the best choice as it is recommended by TOPSIS. The benefit-to-cost ratios are also shown in Figure 9, where ”Securing element” is highly cost-beneficial up to 0.3g, clearly beneficial between 0.35g and

0.45g, moderately beneficial between 0.5g and 0.55g, marginally beneficial between 0.6g and 0.7g, and not beneficial beyond 0.75g.

5. Case study 3: DSS for community earthquake drills and evacuation

Community earthquake drills aim at simulating the scenarios that might accompany a serious earthquake to improve disaster preparedness. This is an opportunity for the community residents to speak freely about scenarios that are too frightening and chaotic. The quality of the drill exercise is dependent on the skills of both planners and participants. Additionally, a large scale community-based earthquake drill has the power to change the political climate of support for such activities (Simpson 2002). It is noted here that another case study that could have been considered in this article was the evacuation of schools or hospitals during periods of heighted hazard. Given the number of uncertain variables involved in such an example it was decided not to consider this here.

Evacuation is the most difficult and disruptive decision that authorities could make prior to an earthquake or during an aftershock sequence. Evacuation as a mitigation action is likely rarely cost-effective (e.g. Van Stiphout et al. 2010). That is why we choose earthquake drills and evacuation as two contrasting mitigation actions to be compared with taking no action. The adapted consequence matrix and the input variables for this situation are summarised, respectively, in Table and Table 8, where we have tried to reduce the parameters in order to undertake a sensitivity analysis to reveal the most influential input variables. As seen in Table , we have assumed that the population of the community is 100,000, that a severe earthquake will cause injuries to 2 per cent of the population and kill 0.4 per cent (Van Stiphout et al. 2010) in the absence of any mitigation actions. The annual cost of an earthquake drill is taken as $150,000, the cost of an injury equal to $10,000 per person, and the cost of a casualty as $1,000,000 per person. Finally, it is assumed that the earthquake drill will reduce the injuries and casualties by a factor of 5, and the evacuation will eliminate the entire risk of casualties and injuries. Evacuation will cost $500 per person per day. Hence, the total evacuation cost is the product of $500, the community population and the duration of the crisis. Two sensitivity calculations will investigate these assumptions in the next section. It is worth emphasising that the downtime criterion is replaced by the casualty criterion in this example, showing the flexibility in the proposed framework.

The results are shown in Figure 10 and Figure 11. As seen in Figure 10, an earthquake drill is recommended for all PGA thresholds and it is preferred over evacuation by a considerable distance. Additionally, the benefit-to-cost ratio for earthquake drills is always greater than unity; however, evacuation, at least within the assumed variables here, is not recommended financially. The level of financial feasibility is shown in Figure 11 where an earthquake drill is highly cost-beneficial up to 0.35g, clearly cost-beneficial between 0.4g and 0.5g, moderately cost-beneficial between 0.55g and 0.7g, and marginally cost-beneficial between 0.75g and 0.85g and not cost-beneficial beyond 0.9g.

Table 7. The adapted consequence matrix for the community earthquake drills and evacuation example (case study 3).

	Direct cost ($)	Number injured	Number of casualties
Earthquake drill	Drill cost	λ_d × (Community population × Percentage injured in large earthquake)/Drill efficiency	λ_d × (Community population × Percentage killed in large earthquake)/Drill efficiency
Earthquake evacuation	Evacuation cost	0	0
No OEF Action	0	λ_d × (Community population × Percentage injured in large earthquake)	λ_d × (Community population × Percentage killed in large earthquake)

Table 8. Input parameters for earthquake drills and evaluation in a community example.

Type of parameter	**Value**
Crisis period	7 days
Community population	100,000
A severe earthquake scenario with 2 % injury and 0.4 % casualty (no action)	
Annual earthquake drill cost	$150,000
Injury cost	$10,000/person
Casualty cost	$1,000,000/person
Annual earthquake drill will reduce the injury and casualty by a factor of	5
Evacuation cost	$500 per person per day
Weightings of each criterion, [Wdirect_cost, Wdeath, Winjury]	[1/3 1/3 1/3]

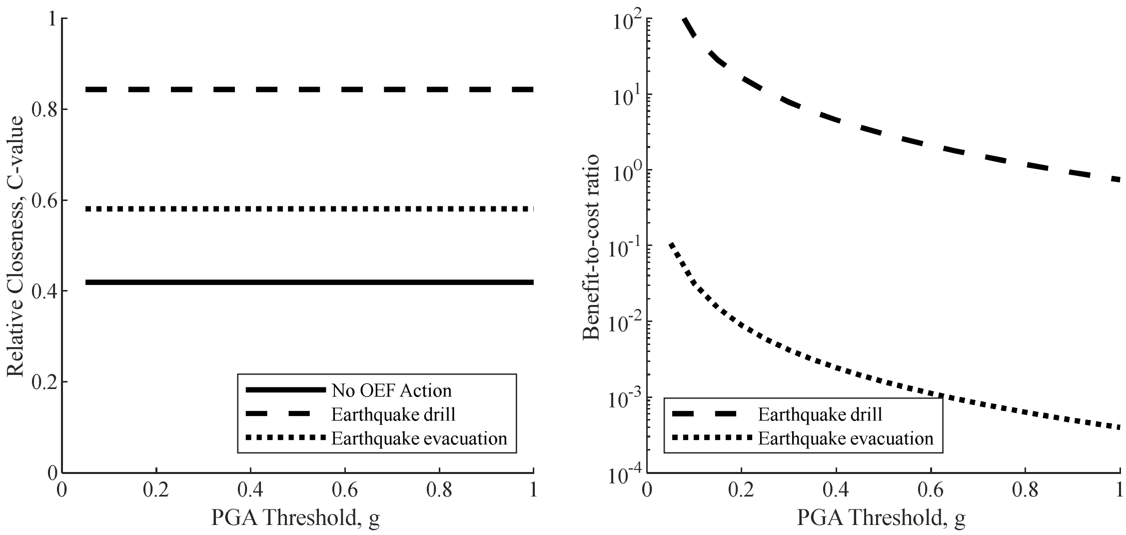


Figure 10. (left): C versus different PGA thresholds, (right): R versus PGA thresholds for different OEF actions for earthquake drills in a community example.

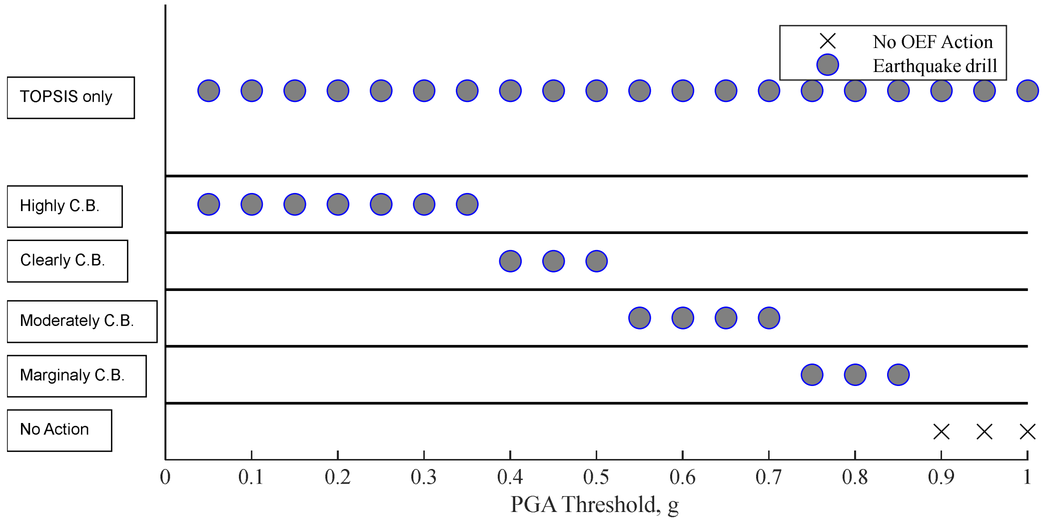


Figure 11. The final result of the TOPSIS only algorithm (top row) and the combination of TOPSIS and cost-benefit analysis for the community example.

5.1. Sensitivity Analysis

A tornado analysis (Howard 1988; Eschenbach 1992) was carried out for this example to find where significant variation could come from so that variables needing further refinement can be spotted and plans can be made to improve their accuracy at a later stage. All but one of the variables was held at its 50th percentile (median) value to carry out the tornado analysis, whilst the variable in question was changed to its 10th percentile and 90th percentile value. The resulting C, corresponding to the earthquake drill mitigation action, were then plotted, making it easy to see the origin of the variation in the output of the DSS. Five input variables are selected for investigation in this example, as summarised in Table . Expert judgments were made for the lower and upper bounds of the investigated parameters in Table .

Table 9. Selected input parameters for sensitivity analysis of earthquake drills in a community example.

Investigated parameter	Lower and upper bounds
Community population	[10,000, 100,000]
A severe earthquake scenario with X % injury (no action)	[.5, 2], % of the population
A severe earthquake scenario with X % casualty (no action)	[.1, .4] , % of the population
Annual earthquake drill cost	[$0.5, $5]/person
Annual earthquake drill will reduce the injury and casualty by a factor of	[1 10]

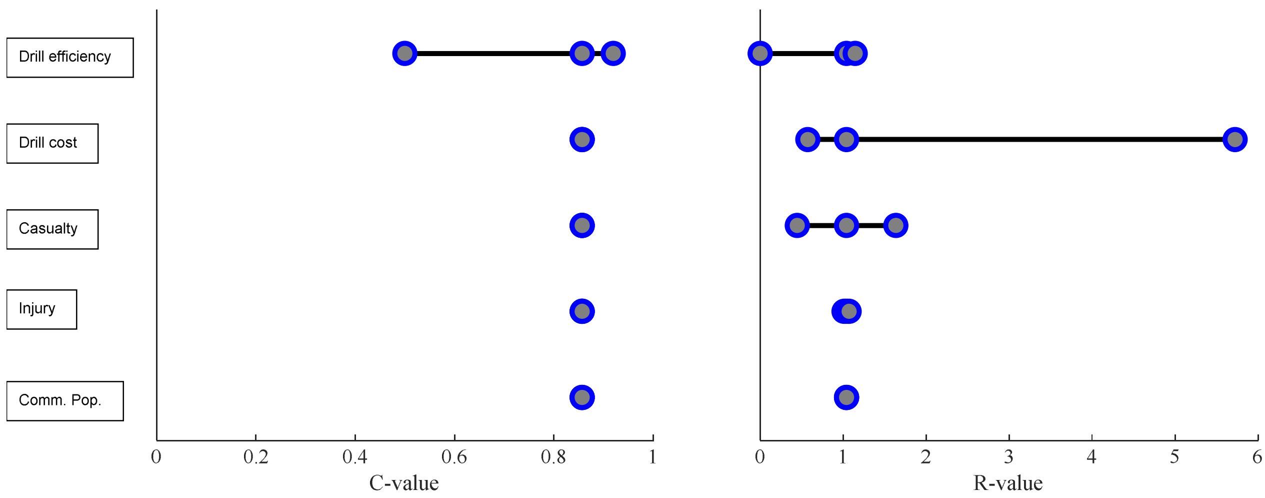


Figure 12. Result of tornado sensitivity analyses for five selected variables in Table and the drill mitigation action.

The PGA threshold is chosen as 0.5g, PG is assumed equal to 10, and an equal weighting scheme has been used. The results revealed that the sensitivity decreases as the PGA threshold increases. The results are shown in Figure 12, in which the variation of C and R are, respectively, shown in the left and right graphs. As it is seen in Figure 12, the drill's efficiency (reducing the casualties and injuries by a certain factor), the drill's cost, and the casualty rate are the most influential variables within TOPSIS. It is worth emphasising that the results are not sensitive to the community population since the injury, casualty, and drilling cost are defined as being proportional to the community's population. However, the drill's efficiency mainly influences the cost-benefit analysis. Therefore, the three top variables (in Figure 12) are chosen for more careful considering using a bootstrap analysis (Efron 1979; Efron and Tibshirani 1994). One thousand samples are randomly generated (the probability distributions shown in **Error! Reference source not found.** are assumed to be uniform distributions), and C and R are calculated using sets of the three investigated variables, i.e. the drill's efficiency, cost, and casualty rate. The results are shown in Figure 13, Figure 14, and Figure 15 by illustrating C (TOPSIS algorithm) and R (cost-benefit analysis).

As seen in Figure 13(left), the more efficient the drill, the more drills are recommended by the TOPSIS algorithm. However, as seen in Figure 13(right), from the cost-benefit point of view, the drill is recommended when the casualties are significant. As a rule of thumb, a drill efficiency of more than six would result in the recommendation of drill by the TOPSIS algorithm. However, a drill is barely recommended when the drill's efficiency is low. Also, financial feasibility increases as the casualty rate increases, as seen in Figure 13(right), e.g. it is more financially justifiable in communities with vulnerable structures. These results demonstrate that the assumed drill efficiency is a key variable.

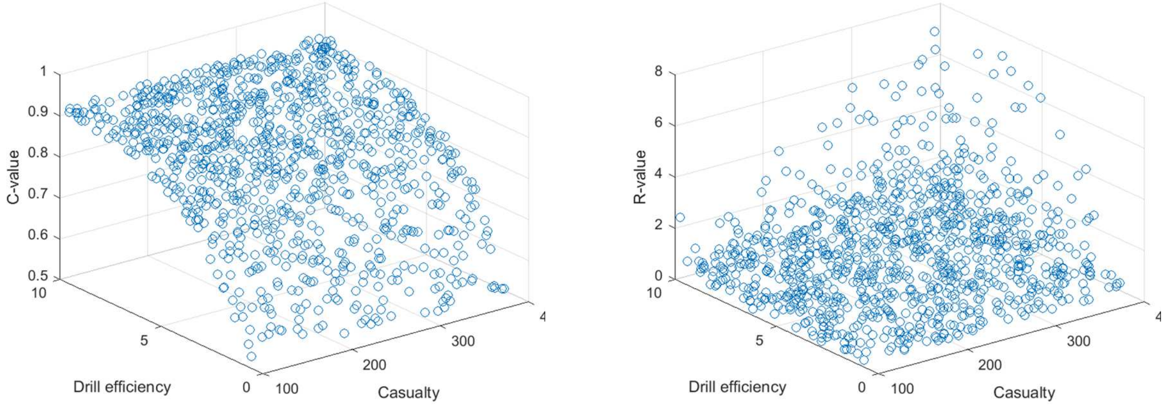


Figure 13. Bootstrap analysis results of C (left) and R (right) versus the drill efficiency and the casualty variables.

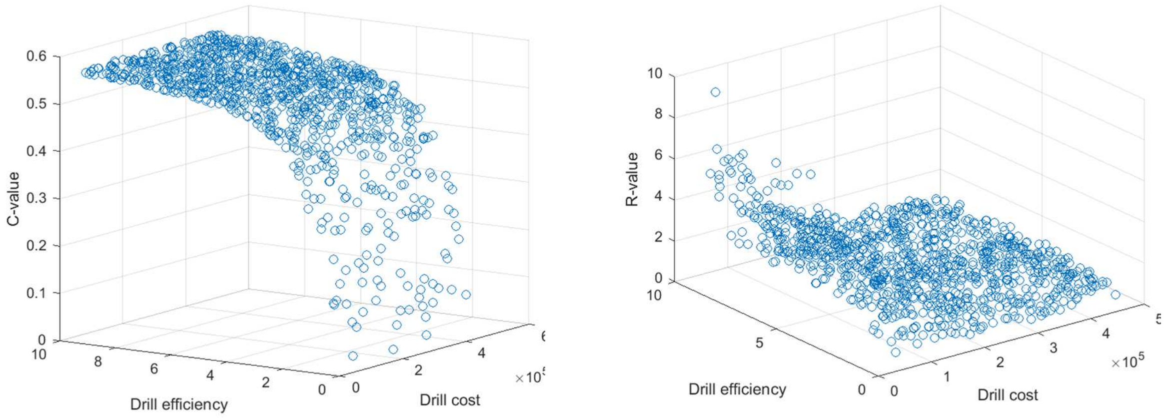


Figure 14. Bootstrap analysis results of C (left) and R (right) versus the drill efficiency and the drill cost variables.

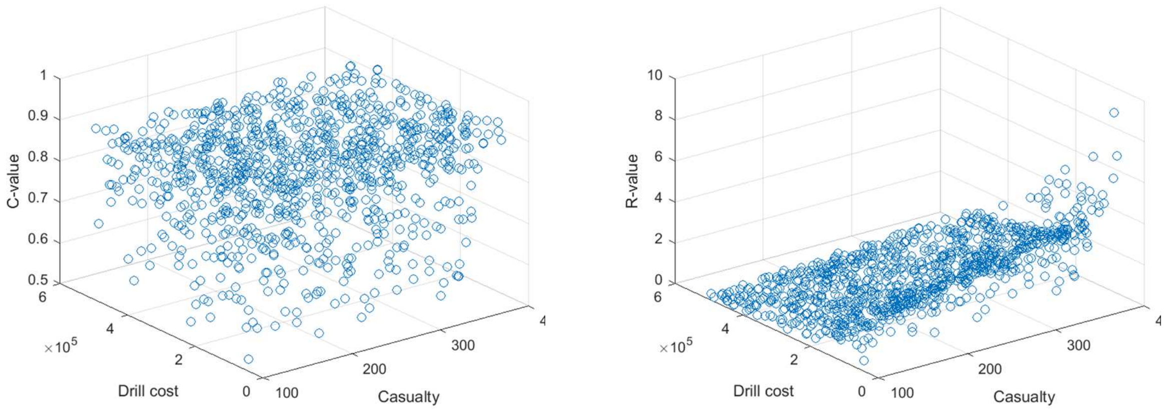


Figure 15. Bootstrap analysis results of C (left) and R (right) versus the drilling cost and the casualty variables.

As seen in Figure 14(left), drill efficiency again controls the results, and the cost of the drill does not play an important role since the cost is assumed proportional to the population. However, a lower drill cost results in higher values of R (more cost-beneficial), as seen in Figure 14(right). Also, drills are highly recommended when the drill efficiency is high, and the drill cost is low. Therefore, it can be concluded that reasonable drill costs with a good drill organisation (high efficiency) can make this mitigation action a logical choice for authorities. As seen in Figure 15(left), there is no meaningful trend between the drill cost and the casualties. However, as shown in Figure 15(right), the highest benefit-to-cost ratios are when the drill cost is low and the casualty rate is high, i.e. small communities with vulnerable structures.

6. Conclusions

This study has introduced a new approach to systematically investigate the effectiveness of mitigation actions during a period of heightened seismicity in the context of operational earthquake forecasting. A recently proposed decision support algorithm for early warning systems has been adapted to the problem of operational earthquake forecasting. This algorithm has been combined with a cost-benefit analysis to examine the financial benefits of the recommended actions. Three hypothetical cases were studied: (1) boxes falling in a warehouse, (2) secondary systems falling from a building, and (3) earthquake drills and evacuation for a community. The results show that mitigation actions are beneficial if damage is caused by low shaking levels and when the actions are cheap enough and can mitigate a significant portion of the underlying risk. Also, a sensitivity analysis has revealed which assumptions have the most influence on the final results. These examples show that the approach has the potential to be adapted to various contexts but that applying the methodology for a specific end user is a vital next step.

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CONFLICT OF INTEREST

There are no conflicts of interest associated with this research.

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