Quantifying the value of SHM for emergency management of bridges at-risk from seismic damage

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Abstract. This paper proposes a framework for quantifying the value of information that can be derived from a structural health monitoring (SHM) system installed on a bridge which may sustain damage in the mainshock of an earthquake and further damage in an aftershock. The pre-posterior Bayesian analysis and the decision tree are the two main tools employed. The evolution of the damage state of the bridge with an SHM system is cast as a time-dependent, stochastic, discrete-state, observable dynamical system. An optimality problem is then formulated how to decide on the adoption of SHM and how to manage traffic and usage of a possibly damaged structure using the information from SHM. The objective function is the expected total cost or risk. The paper then discusses how to quantify bridge damage probability through stochastic seismic hazard and fragility analysis, how to update these probabilities using SHM technologies, and how to quantify bridge failure consequences.

Keywords: Bridges, pre-posterior analysis, seismic damage, seismic risk, seismic structural health monitoring, value of information

1 Introduction

Structural health monitoring (SHM) has gained considerable interest in the technology research and development community. Because of this technology push, SHM has made a transition from the laboratory to the real world and many in-situ structures, notably bridges, have been instrumented. However, most of such monitoring exercises are academically driven and practitioners, asset managers and emergency response authorities (e.g. those charged with ensuring adequate post-earthquake actions) remain indifferent to the practical usefulness and value of SHM. At the same time, strong assertions can be heard about the value and expected benefits of SHM. It is thus important that the claims of the value of SHM be backed up by quantitative evidence, otherwise the idea of SHM may be seen by sceptics, not just opponents, as belonging largely in the post-truth world.

The broader motivation behind using SHM is to collect information about structural performance and condition, that would otherwise be unavailable or of insufficient accuracy or precision, and use this information for managing the risk of infrastructure failure or underperformance. If so, the concept of risk can be, as a function of both the probability of failure and its consequences, utilized in quantifying the value of SHM given the many uncertainties encountered in processing SHM data for structural failure prediction, SHM system performance (e.g. accuracy of the data measured and models used) and failure consequences. A useful tool, which utilizes the concept of risk, is the Bayesian pre-posterior decision analysis combined with the decision tree representations, as this enables calculating the value of SHM information even *before* one procures and installs an SHM system. The fact that we are trying to evaluate the performance and economic benefit of an SHM system that has not yet been deployed on a structure is critical to appreciate the use of pre-posterior decision analysis, but it may initially elude the reader. However, it is, in fact, not dissimilar to, e.g. seismic risk analysis, where we try to model probabilistically what could happen should an earthquake occur, but we do so *before* the actual event. Indeed, performance-based seismic design or assessment of a structure is a similar undertaking, where we try to envisage what could happen to a structure that now only 'exists' in the designer's minds, and make decisions about what to do to manage the risks potentially eventuating. In *all* those cases, we deal with significant uncertainties.

In this paper, the Bayesian pre-posterior decision analysis is employed to propose a framework for quantifying the value of using SHM in the context of detecting damage to bridges subjected to strong ground motion for achieving better-informed post-event decisions such as those pertaining to the continuation of full or limited emergency operations or bridge closure because of safety concerns. The framework uses the established seismic structural risk analysis principles based on site hazard probabilities and structural vulnerabilities, and absorbs SHM information into the process. An important aspect is that aftershock induced hazard is considered. After the occurrence of a mainshock earthquake, the affected area will often experience an increased level of seismic activity with a potential large number of strong aftershocks. Such sequences of aftershock events may continue for several months in case of large magnitude mainshock events. A bridge exposed to the mainshock or earlier aftershocks may have been damaged by them and will now have increased vulnerability to future tremors. Thus, one example scenario where SHM could make a difference is detecting such existing damage so that the weakened, but still operating, structure does not fall in an aftershock, leading, e.g., to new casualties or injuries amongst its users and other avoidable consequences. We assume that only seismic risk is considered, i.e. the bridge will not fail under traffic or other loads, but the framework can be extended to include multiple hazards, as it can to consider also structural deterioration with time due to corrosion, fatigue or scour.

2 Framework for quantifying the value of seismic SHM of bridges

This section presents a process of building a decision tree for the Bayesian pre-posterior analysis (Raiffa & Schlaifer, 1961) for quantifying the value of seismic SHM of bridges. It starts with a decision problem whether a bridge should be closed or kept in service for a structure subjected to the mainshock and a single aftershock when SHM is not used. It then considers how additional information from SHM may be used in emergency decision making. The evolution of the damage state of the bridge with an SHM system is cast as a time-dependent, discrete-state, observable, stochastic dynamical system. An optimality problem is thus formulated how to decide on the adoption of SHM and how to manage traffic and usage of a possibly damaged structure incorporating SHM data where it is available. The objective is to find a set of decisions that lead to the minimum expected total cost including the price paid for installing and maintaining SHM system and the probable losses that ensue due to the operational decisions made.

2.1 Decision problem for continuing operations of a bridge without an SHM system subjected to the mainshock and a single aftershock

The decision tree used in the situation described in the section title may be build up as a collection of the basic blocks shown in Figure 1. On the left, the detail of the basic building block is shown, and on the right, its abridged symbolic representation. Squares denote decision nodes and circles represent random outcome nodes. To keep the schematic representation uncluttered, only some branches of the tree are shown; similar simplifications will be used throughout the paper. The generic symbol E (also when used as a superscript) refers to a particular *event*: E=M for the mainshock, and E=A for the aftershock, respectively. TR_i^E refer to *traffic restriction* actions taken by the authority after the seismic event E. There may be $K+1$ different actions, with TR_0^E corresponding to uninterrupted operations, and, at the other end, TR_K^E corresponding to the full closure of the bridge; the other actions could be restricting the use to only light vehicles and/or restricting speed, allowing only use by emergency vehicles, etc. Note, these decisions must be reached, in the scenarios considered in this section, using only the information which is available without a dedicated SHM system installed on the bridge. DS_i^E refer to levels of *damage sustained* by the structure during seismic event E. The level of damage is often expressed by assigning the structure to one of the L+1 discrete damage states, ranging from, e.g. no/negligible damage, to light damage, to moderate damage, to severe damage, and eventually to the total collapse. Alongside the different levels of damage, shown are the probabilities of their occurrence, P^E_{DSi}.

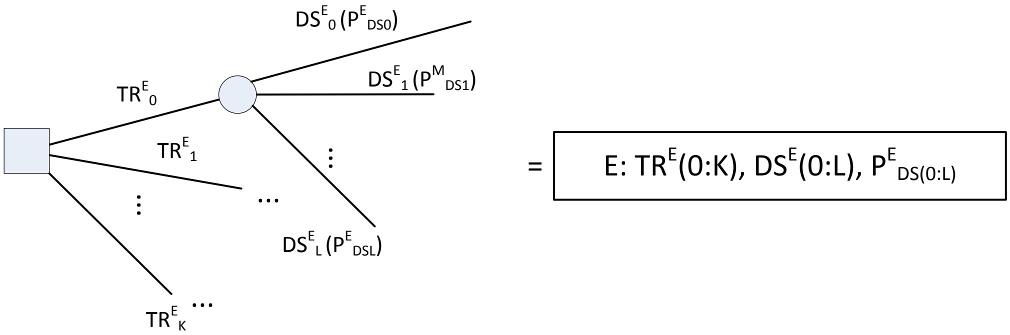

Fig. 1. Basic building block of decision tree to manage bridge usage

The full decision tree for continuing operations of a bridge without an SHM systems subjected to the mainshock and a single aftershock is shown in Figure 2. Here, in the building blocks for the aftershock events (denoted by symbol *A*), the probabilities $P^{A|M}_{DS_i|DS_j}$ of bridge sustaining a given level of damage, DS_i in the aftershock are conditional on the level of damage, DS_j sustained in the mainshock, i.e. they are transition probabilities. That in fact cast our problem as a dynamical, discrete-state stochastic system. Without monitoring, the system is not observable, but once an SHM information is included, which is explained in the following section, it will become observable. The system can be though as time dependent, although this is now hidden in the occurrences of the mainshock and the aftershock. This also expresses the fact that damage will accumulate over consecutive earthquakes. On the very right of Figure 2 are consequences related to each combination of actions and random outcomes (states of nature), $C_{ijkl} = C\left(TR_i^M, DS_j^M, TR_k^A, DS_l^A\right)$, ($i$, k=0, 1, … K; j, l=0, 1, … L). For example, closing the bridge altogether to traffic after the mainshock or the aftershock, when in fact it can be used without restriction or perhaps at least for emergency services, will entail economic losses because of delays, loss of service etc., and will possibly also mean delays in getting the injured to a hospital worsening their condition. On the other hand, a bridge that is unsafe but allowed to operate may collapse leading to additional economic losses or even casualties or new injuries.

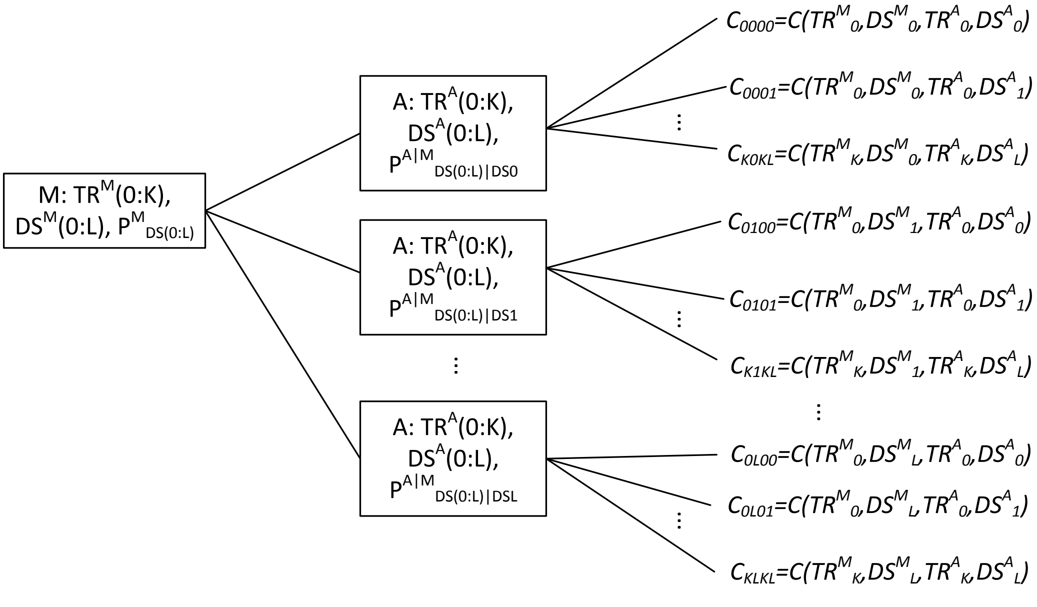

Fig. 2. Decision tree for continuing bridge operations for bridge without SHM system subjected to mainshock and aftershock

The optimal pair of actions $\left(TR^M, TR^A\right)_{opt}$ after the mainshock and the aftershock is the one that minimizes the overall risk:

$$\left(TR^M, TR^A\right)_{opt} = \min_{i=0,1\ldots K} E_{DS_j^M} \min_{k=0,1\ldots K} E_{DS_l^A|DS_j^M}\left[C_{ijkl}\right] \tag{1}$$

Here, E[] denotes the expected value operator.

2.2 Decision problem for continuing operations of a bridge with an SHM system subjected to the mainshock and a single aftershock

To handle the scenario where an SHM system is to be adopted, another basic decision tree building block is adopted as shown in Figure 3. Here, decisions to adopt a *health monitoring* system before seismic event E are denoted as HM_i^E. There may be N+1 such decisions, each corresponding to the adoption of a particular SHM system or technology, with HE_0^E corresponding to the decision to not adopt any. Note that the superscript E is still present as we envisage monitoring may be adopted before the mainshock but alternatively only after the mainshock to monitor the structural performance and damage in the aftershock of the bridge weakened in the mainshock (in which case it would be replaces by superscript A). The cost of each system is indicated by C_{HMi}, with C_{HM0}=0. It should be noted that for a fair assessment of the cost involved in monitoring a structure not only the cost of hardware (capex) must be included but the whole life-cycle cost needs to be quantified (design, installation, operational costs including maintenance, decommissioning, etc.), and the cost of data analysis and integration of the SHM information into the emergency response process. DD_i^E refer to *damage detected* by the monitoring system. Again, it is envisaged that based on the SHM system indication, the structural state will be mapped into one of the L+1 discrete detected damage states. The probabilities of indication of the different levels of damage are indicated as P_{DDi}^E. Note these probabilities include correct as well as incorrect detected damage state classifications with respect to the actual damage states the structure will find itself in.

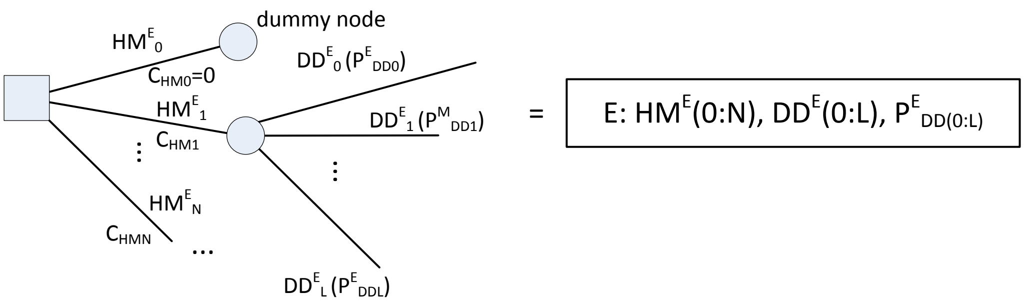

Fig. 3. Basic building block of decision tree for SHM system adoption

With the newly introduced additional building block, we can now formulate the full decision tree for adoption of an SHM system. It is shown in Figure 4. The consequences at the far-right end, $C_{ijklmnpr} = C\left(HM_i^M, DD_j^M, TR_k^M, DS_l^M, HM_m^A, DD_n^A, TR_p^A, DS_r^A\right)$, ($i$, m=0, 1, … N; j, l, n, r=0, 1, … L; k, p=0, 1, … K), depend now also on the additional decisions to adopt or not an SHM system, and if so which, and random outcomes include damage detection alerts issued by the SHM system. As one moves from left to right, the probabilities of each damage state being indicated or actually sustained depend on the entire history of preceding decisions and random outcomes.

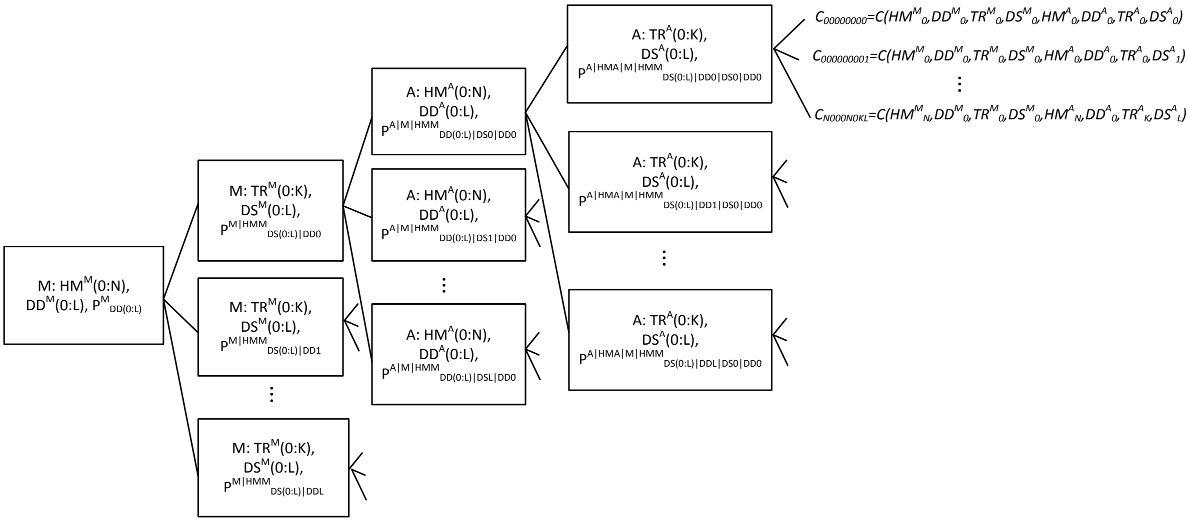

Fig. 4. Decision tree for continuing bridge operations for bridge with SHM system subjected to mainshock and aftershock

The conditional probabilities $P_{DSi|DDj}$ of damage state DS_i having actually been sustained when damage state DD_j has been indicated by the SHM system appearing in the decision tree may be found from the state probabilities $P_{DS_i}^{M}$ and state transition probabilities $P_{DS_i|DS_j}^{A|M}$ (i, j=0,1,…L), and the probabilities $P_{DD_j|DS_i}$ of correct/incorrect indications of damage states by the monitoring system, for example:

$$P_{DD_j}^{M} = \sum_{i=0}^{L} P_{DS_i}^{M} P_{DD_j|DS_i}^{M} \tag{2}$$

$$P_{DS_i|DD_j}^{M|HM^M} = \frac{P_{DS_i}^{M} P_{DD_j|DS_i}^{M}}{P_{DD_j}^{M}} \tag{3}$$

The optimal set of actions $\left(HM^M, TR^M, HM^A, TR^A\right)_{opt}$ is the one that minimizes the overall risk:

$$\left(HM^M, TR^M, HM^A, TR^A\right)_{opt} = \min_{i=0,1...N} E_{DD_j^M} \min_{k=0,1...K} E_{DS_l^M|DD_j^M} \min_{m=0,1...N} E_{DD_n^A|DS_l^M|DD_j^M} \min_{p=0,1...K} E_{DS_r^A|DD_n^A|DS_l^M|DD_j^M} \left[C_{ijklmnpr}\right] \tag{4}$$

3. Bridge seismic risk modelling: hazard and fragility for

The probability $P_{DS_i}^{E}$ of a bridge sustaining damage state DS_i when subjected to an earthquake during its expected service life is a critical parameter in the proposed framework (see Figure 1). This probability is a function of hazard at the site and fragility of the bridge. The probability $P_{DS_i}^{E}$ can be estimated using the following expression:

$$P_{DS_i}^{E} = \int_{0}^{+\infty} \left[F_{D|IM}\left(d_i \,|\, x\right) - F_{D|IM}\left(d_{i+1} \,|\, x\right)\right] \left|\frac{\mathrm{d}\lambda_{IM}(s)}{\mathrm{d}s}\right|_{s=x} dx \tag{5}$$

In the expression above, $F_{D|IM}(.|.)$ is the cumulative conditional probability distribution of peak demand, D, imposed on the bridge conditioned on the intensity measure, IM, of strong ground motion at the site. Variables d_i and d_{i+1} are the demand levels (e.g. strains, curvatures, displacements) corresponding to the onset of damage states DS_i and DS_{i+1}, respectively. The expression $|\mathrm{d}\lambda_{IM}/\mathrm{d}s|$ is the absolute value of the derivative of the estimated seismic hazard λ_{IM}. Typical IM parameters are pseudo-spectral acceleration of the equivalent damped single-degree-of-freedom system, $S_a(T)$, peak ground velocity, PGV, and peak ground acceleration, PGA. IM establishes the connection between the hazard and the vulnerability. Therefore, it is critical to adopt a measure that can effectively capture the seismic behavior of the bridge and can be probabilistically estimated with an acceptable level of uncertainty. Benefits and limitations of alternative *IM*s are discussed by Weatherhill et al. (2011). In the following, potential strategies for estimating the seismic hazard, λ_{IM}, and the fragility, $F_{D|IM}$, will be presented.

The seismic hazard at the site of the bridge can be estimated by performing a probabilistic seismic hazard assessment (PSHA) as proposed by Cornell (1968). In PSHA, the rate, λ_{IM}, at which the strong motion intensity, *IM*, at the site is expected to exceed a specific level, *s*, within a fixed time is assessed. The rate λ_{IM} is evaluated using the following expression:

$$\lambda_{IM}(s) = \sum_{i=1}^{n_s} \nu_i \int_{m_{\min}}^{m_{\max}} \int_{0}^{r_{\max}} P\left[IM > s \middle| m, r\right] f_{R|M}\left(r \middle| m\right) f_M\left(m\right) dm\, dr \tag{6}$$

where n_s is the number of seismic sources that are expected to induce significant shaking at the site, ν_i is the rate of earthquakes that occur at the *i*-th source and which have magnitudes within the range bounded by the minimum magnitude, m_{min}, and the maximum magnitude, m_{max}. The term $P[IM > s|\, m, r]$ is the conditional probability of shaking intensity *IM* at the site exceeding level *s*, given that the site is excited by an earthquake of magnitude *m* and with a rupture plane that lies at a distance *r* from the site. This probability is estimated using ground motion prediction equations which aim at capturing the expected attenuation or amplification of the seismic waves which propagate along the path from the source to the site (Kramer, 1996). Probability density $f_M(m)$ is equal to the relative likelihood of magnitudes of earthquakes that occur within considered time being equal to *m*. Likewise, $f_{R|M}(r|m)$ is the conditional probability of the source-to-site distance being equal to *r* for an earthquake with magnitude *m*.

In the proposed framework, seismic hazards associated with two different types of earthquakes are considered, namely the mainshock and the aftershock earthquakes. Large magnitude earthquakes are often preceded and succeeded by smaller magnitude events that occur at the proximity of each other and within a short period. An entire sequence of earthquakes is referred to as a cluster. Within a cluster, the event with the greatest magnitude is named the mainshock and all the following earthquakes are called aftershocks. Existing earthquake catalogs suggest that mainshock earthquakes often occur at a relatively constant rate at seismic source zones. Accordingly, these events are typically modelled as a homogeneous Poisson processes in the conventional PSHA. Hence, the probability $P_{DS_i}^{M}$ - related to the mainshock - can be obtained using λ_{IM} obtained from Equation (6) and considering structural vulnerability or fragility.

The aftershock earthquakes occur at a rate that decays with time elapsed since the mainshock. The characteristics of this decay were first systematically investigated by Omori (1894). Even today, Omori's model is frequently used for modeling the decaying of rate of aftershocks. Since the rate of aftershocks is not constant over time, the aftershock events are modelled as a non-homogenous Poisson processes in the PSHA. Yeo and Cornell (2009) proposed a modified version of PSHA that considers the time dependent decay of the rate of events. Recently, Müderissoglu and Yazgan (2017) developed a modified version of this approach, which enables making use of mainshock strong motion recordings in updating the uncertainty associated with the expected attenuation of the aftershock induced shaking. This updating results in changing of the conditional likelihood $P[IM>s|m,r]$ in Equation (5). In case of bridges designed and constructed according to modern seismic codes, the primary source of uncertainty associated with the expected performance is that due to uncertainty of the estimated hazard. Therefore, such an updating of the uncertainty associated with the hazard estimate would often lead to a considerable change in the predicted seismic performance.

The aftershock hazard assessment method developed by Müderrisoglu and Yazgan (2017) is especially suitable for bridges which have free-field strong motion recoding instruments. In the context of the framework proposed here, such instrumentation may be conceived as a part of the monitoring system. Using the method, the ground motion recorded by the free-field sensor can be utilized to revise the uncertainties associated with the expected level of attenuation. Thus, the aftershock hazard conditional on the recorded mainshock motion can be obtained. When compared to the case with no instrumentation, this conditional hazard estimate would result in higher or lower exceedance rates.

This difference depends on the motion intensity level registered during the mainshock event. The aftershock damage probabilities, $P^{A|M}_{DS_j|DS_i}$, corresponding to the decision tree branch in Figure 4 related to not adopting any monitoring system (i.e. HM_0^M) may be evaluated using the conventional aftershock hazard assessment approach by Yeo and Cornell (2002). On the other hand, the probabilities $P^{A|M}_{DS_j|DS_i}$ corresponding to the branches related to adopting a monitoring system (i.e. HM_i^M, i=1,2,…N) can be evaluated by substituting the λ_{IM} estimates obtained using the method by Müderrisoglu and Yazgan (2017) into Equation (5).

The conditional probability of a bridge sustaining damage state DS_i when subjected to a given level of shaking intensity is referred to as the seismic fragility. This conditional probability is represented by the term $F_{D|IM}(.|.)$ in Equation (5). There exists a large variety of methods proposed for assessing seismic fragility of structures (Porter, 2003). In the proposed framework, an approach that can be applied to individual structures is needed. Moreover, the approach should enable rational consideration of various sources of uncertainty that have significant impact on the estimated likelihood $F_{D|IM}$. Based on these constraints, the 'analytical approach' for fragility modeling is particularly suited to the framework presented here.

In the analytical fragility modeling approach, a basis numerical model of the bridge is developed for seismic response analysis. The uncertainties associated with the model are assessed and probability distributions are established to capture their random variability. Typically, the existing recommendations (e.g. JCSS, 2001) are utilized for this purpose. A set of alternative models are generated using these probability distributions. Subsequently, a suite of strong ground motion records is established. The records are selected to capture with a required accuracy the mean value and dispersion of the seismic response of the bridge that will be exhibited when it is subjected to the expected seismic events during its service life (Kalkan & Chopra, 2010). For each randomly generated model with a ground motion, incremental dynamic analysis (Vamvatsikos & Cornell, 2002) can be performed. In this process, the response of the bridge to the specific ground motion is simulated by gradually scaling up the ground motion to different IM levels. The record is scaled to the level when the computed demand becomes just equal to the threshold d_i associated with the onset of damage state DS_i. The intensity level x'_{di} that correspond to this threshold is determined for all model realization and ground motion record pairs. Subsequently, the fragility is evaluated as follows:

$$F_{D|IM}\left(d_i \,|\, x\right) = \Phi\left(\frac{x-\mu_i}{\sigma_i}\right), \text{ where } \mu_i = \frac{1}{n_m}\sum_{j=1}^{n_m} x'_{di}\left(j\right) \text{ and } \sigma_i = \sqrt{\frac{1}{n_m - 1}\sum_{j=1}^{n_m}\left[x'_{di}\left(j\right) - \mu_i\right]^2} \tag{7}$$

In the equation above, $\Phi(.)$ is the standard normal distribution function, μ_i and σ_i are the mean and standard deviation of the IM levels that correspond to the onset of DS_i, and n_m is the total number of model and record pairs. The fragility estimates related to both damage state DS_i and the next more severe one DS_{i+1} needs to be substituted into Equation (5) in order to evaluate the probability $P^M_{DS_i}$ of the bridge sustaining damage state DS_i. The damage probability $P^M_{DS_i}$ is obtained by considering the response of the intact bridge to the mainshock event.

The likelihood $P^{A|M}_{DS_i|DS_j}$ of the mainshock induced damage grade DS_i progressing to a higher grade DS_j because of aftershock induced shaking is needed in the proposed framework. Evaluation of the conditional probability $P^{A|M}_{DS_i|DS_j}$ for a bridge is a more challenging task compared to evaluation of $P^M_{DS_i}$. In this evaluation, the fragility analysis needs to be performed using a damaged bridge model rather than an intact one. Specifically, the damage imposed on the model should be of grade DS_i. The actual mainshock motion that will impose this damage during the expected service life is not available at the time of assessment. The damage grade is a global measure of damage while the actual seismic response is sensitive to all local damages within critical locations combined. Thus, different ground motion records may damage critical zones of the bridge to varying extents as they impose the same global damage state DS_i. In the evaluation of conditional likelihood $P^{A|M}_{DS_i|DS_j}$, this record-to-record variability of mainshock motions that impose the same DS_i grade needs to be considered. One strategy to achieve this is to establish a set of mainshock motions and identify the scaling factors for each of these motions that correspond to the onset of damage state DS_i. Subsequently, aftershock fragility analysis is performed by simulating the response of each randomly generated structural analysis model to sequences of ground excitations. This sequences should consist of the mainshock shaking that imposes damage state DS_i followed by an aftershock excitation (Ryu et al., 2011). The specific aftershock shaking intensity level x'_{dj} that corresponds to the onset of damage state DS_j, is identified by repeating this analysis for a range of aftershock scaling factors. In this analysis, the polarity of aftershock excitation should be randomized as recommended by Ryu et al. (2011). It should be born in mind that the process entails considerable computational effort. To reduce this effort, an approach based on nonlinear regression recommended by Alessandri et al. (2013) may be adopted.

After the intensity levels x'_{dj} are identified for all the mainshock-aftershock sequences, Equation (7) may be utilized to establish the aftershock fragility of the bridge. In this case the resulting fragility $F_{D|IM;DSi}(d_j|x;DSi)$ is conditioned on the mainshock induced damage state DS_i. The required conditional probabilities $P^{A|M}_{DS_i|DS_j}$ can be obtained by substituting $F_{D|IM;DSi}(d_j|x;DSi)$ into Equation (5).

4. Probability of damage state classification and integration of SHM data into bridge reliability assessment

Quantifying the value of SHM via the Bayesian pre-posterior analysis as described in this paper and integration of SHM data into bridge reliability assessment requires probabilities $P^{E}_{DD_i|DS_j}$ of classification of structural states based on the indication from the SHM system. These can generally be found from probability distribution functions of a damage indicator corresponding to the different actual damage states (Omenzetter et al. 2016). These probability distributions will be dependent on the particular SHM system adopted. Here, we need to consider the whole process of SHM data collection and processing which output a damage state indicator. There are a number of challenges at this point as discussed below.

The various structural damage states are known to correlate better with measures related to structural displacements or rotations and associated ductilities, the latter particularly relevant for modern structures designed for seismic regions. For example, Table 1 (Banerjee & Shinozuka, 2008) shows classification of damage into several states depending on the rotational ductility demands. Yet measuring displacements or rotations in-situ for large structures presents a considerable practical challenge, mostly because a fixed reference base is difficult to find for contact measurement technologies, such as linear variable displacement transducers. Non-contact devices will often require a stable base too, which may not be easily available in seismic monitoring, and unobstructed line of sight, which is often unavailable due to vegetation, complex terrain or in densely built-up environs. The global positioning system does not yet offer accuracies required in our context. Strain gauges, and other types of attachable sensors for that matter, will not survive in the areas of large deformations – where we would ideally like them to be placed - because of cracking and spalling. On the other hand, the type of measurements that are more readily available, notably accelerations, do not yield features that readily map quantitatively into structural damage states. Double integration of acceleration time histories to obtain displacements is fraught with drifts. Any practically useful framework for quantifying the value of seismic SHM must recognize such practicalities.

Table 1. Damage states and corresponding rotational ductility demands (adopted from Banerjee & Shinozuka, 2008)

Damage state	Rotational ductility demand
None	<1
Negligible	1-1.52
Minor	1.52-3.10
Moderate	3.10-5.72
Major	5.72-8.34
Collapse	>8.34

A damage detection/classification and future reliability prediction solution that uses acceleration measurements combined with structural model updating and nonlinear time history analysis to establish the probabilities of correct and incorrect classification of structural state based on the indication from the SHM system is proposed here by extending the earlier work of Soyoz and his collaborators (Soyoz et al., 2010, Kaynardag & Soyoz, 2015; Özer & Soyoz, 2015). The approach adopted comprises the following steps:

- A nonlinear finite element (FE) model of the bridges is formulated. This model may also include effects such as soil-structure interaction if deemed important.
- When acceleration data captured by and SHM system becomes available it is used as input to a system identification algorithm to determine modal properties (natural frequencies, damping ratios and mode shapes). Note the type of data applicable for this step is from low level excitations such that the linear response regime prevails. It may be an output-only system identification, but if ground motion sensors are installed next to the bridge and/or on its foundations as part of the SHM system, input-output methods can be adopted that can improve the reliability of results. Enhanced system identification approaches may include considering environmental and operational effects on the responses, such as temperature or presence of vehicles on the deck.
- The FE model initial stiffness is calibrated (updated) against the identified modal parameters. Note because of the linearity limitation above other model parameters that govern the nonlinear part of the response cannot be inferred directly using this approach.
- The updated model is run for nonlinear time history analyses to identify the fragility of the calibrated model. In these analyses, the damage states are established based on, e.g. ductility of the numerically simulated response (Table 1).

Some sources of uncertainties propagating into potential misclassification errors and affecting $P^{E}_{DD_i|DS_j}$, such as the level of noise in acceleration sensor measurements, can be garnered from laboratory trials and previous field applications. In a similar way, uncertainties in modal system identification results (Chen et al., 2014; Chen et al., 2015) and numerical model updating procedures (Shabbir & Omenzetter, 2016) can be assessed. A 'trial' monitoring system can be installed to gather more site-specific data and reduce uncertainties, but a decision to do so should then be assessed for cost-benefit within the proposed decision making framework. However, beyond those the methodology will have very limited access to experimental validation data. Note we try to make inferences about the performance of an SHM system before we actually deploy it on the structure, thus have no 'hard' measured data. Since large structures such as bridges are unique, even available data or experience from 'similar' structures will have limitations. In any case, there is very little monitoring data available thus far from bridges that actually sustained seismic damage. Circumventing this major challenge will require relying on extensive probabilistic numerical simulations, where the given structural system with all expected uncertainties will be simulated for random combinations of structural properties and ground motion inputs to determine its 'virtual' acceleration responses. These responses will then be fed into the bullet-point procedure outlined above to obtain the detected damage state DD_i results for each response simulation. Afterwards, the resulting detected damage states will be compared to the 'actual' damage states DS_i obtained directly from the structural model obtained using ductility thresholds such as those in Table 1. It is clear that many an assumption will be made in this approach, and that formidable computational effort must be reckoned with in the pre-posterior analysis stage to map the measurements to failure probabilities. However, it should also be recognized that the actual operation of the damage classification system does not necessarily entail running the time consuming nonlinear time history analyses. Based on such analyses during the decision-making stage, relationships, e.g. utilising artificial neural networks, can be built between the identified stiffness loss, or even just recorded ground and response intensity measures like *PGA* and peak structural response acceleration, and failure probabilities for quick, near real-time estimation of the associated risks (de Lautour & Omenzetter, 2009).

5. Bridge seismic risk modelling: consequences of bridge failure

A broad overview of the various bridge failure consequences is presented in Imam and Chryssanthopoulos (2012), and this short discussion is based on their work, while more emphasis is placed here on these aspects that are of particular importance or are more specific to seismic failure consequences. It must be made clear at the onset of any consideration of bridge failure consequences that their modelling is multifaceted, complex and inherently uncertain.

The consequences can be categorized into four main groups: human, economic, environmental and social. Example of the most important consequences in each category are shown in Table 2.

Table 2. Consequences of bridge failure (adopted from Imam and Chryssanthopoulos (2012))

Category	Example
Human	Deaths Injuries Psychological trauma
Economic	Repair or replacement costs Loss of functionality/downtime Traffic delay/re-routing/management costs Clean up costs Rescue costs Regional economic losses Loss of production/business/opportunity Investigations/compensations Loss of other infrastructure services (e.g. electricity, communication cables carried by the bridge)
Environmental	CO_2 emissions Energy use Pollutant releases Environmental clean-up/reversibility
Social	Reputational damage Diminished public confidence in infrastructure Undue changes in professional practice

One important factor that influences bridge seismic damage consequences is that earthquakes affect larger areas simultaneously. Thus, e.g. casualties and injuries can be not only to those who happen to be on, under, or in the vicinity of the collapsing structure, but the loss of functionality of a bridge located on a critical route to a hospital can lead to further human consequences. Furthermore, a single structure is normally just one node of an interdependent transportation network. Other bridges located in the same area will also be exposed to seismic risk, and their potential loss of functionality will affect the traffic demands imposed on our focus structure. To quantify the expected number of people in need of hospitalisation in an aftermath of an earthquake, it will thus be necessary to perform a seismic risk study for the entire area the bridge may be expected to serve in such emergency (e.g. to estimate the number of collapsing buildings) and also simulate the functionality of the transportation network in the earthquake aftermath. Similarly, the direct cost to repair or even replace a bridge may be relatively low for a small and simple structure, but if the structure is located on an important route in a transportation network with poor redundancy, which furthermore can be impaired because of seismic damage to other bridges, the resulting economic losses due to traffic delays, detours and loss of business can be much more significant. These costs can also be widespread, affecting negatively the economy of entire regions, if, for example, the bridge is on a route serving a major sea port. Larger timescales, in the order of several years, for the consequences to unfold may need to be considered as rebuilding after earthquakes can take a significant amount of time.

6. Conclusions

We have outlined a framework for quantifying the value of information from SHM technology installed on a bridge. The general case we consider is that of a bridge structure that may sustain damage in the mainshock and further progressing damage in an aftershock. The value of SHM information is computed using the Bayesian pre-posterior approach to decision making. The evolution of the damage state of the bridge with an SHM system is conceptualised as a time-dependent, stochastic, discrete-state, observable dynamical system. Optimal decisions whether to adopt SHM and how to restrict traffic on a potentially damaged structure is formulated to minimise the expected total cost or risk. The paper then discusses how to estimate the bridge damage probability through stochastic seismic hazard and fragility analysis, and how to update these probabilities using SHM data through an approach that combines modal system identification, structural model updating and nonlinear time history simulations. Finally, a brief overview of quantifying bridge failure consequences is included.

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