Seismic Assessment using a Bayesian Network

Y. C. Yue, M. Pozzi, D. Zonta, F. Bortot& R. Zandonini
DIMS, University of Trento, Italy

ABSTRACT: This paper presents a framework for seismic vulnerability assessment based on Bayesian Networks. This framework incorporates the HAZUS model, the demand model and the capacity model, which are used to calculate the probabilities of earthquake-induced bridge damage. The framework is here applied to 'twin' bridges that are correlated with the demand model and the capacity model. The paper investigates how the observation of the damage occurred on one bridge affects the estimate of the reliability of the other. Generally the framework can be used to update the seismic risk of bridges in post-earthquake scenarios with a limited number of observations.

1 INTRODUCTION

1.1 *Background and motivation of this research*

The Autonomous Province of Trento Bridge Management System (APT-BMS) has been operational since 2004; it manages 1017 bridges and approximately 2400 kilometers of roads. The APT-BMS is capable of seismic vulnerability analysis, based on the definition of fragility curves; these are developed using a capacity-spectrum approach under HAZUS guidelines (FEMA 2003). Using this model, the seismic vulnerabilities of all bridges in APT-BMS were analyzed. In APT-BMS, we consider three earthquake scenarios, with return periods of 72 years, 475 years, and 2475 years respectively. The probabilities of being in one of the four damage states, operational (OLS), damage control (DLS), life-safety (LLS), and collapse (CLS), are calculated. (For more details of the seismic vulnerabilities in APT stock, see Yue et al. 2010).

As we can expect, the seismic vulnerabilities of any two bridges are very similar when they have similar characteristics as to type, material, and construction year; on-site inspection shows that the conditions of similar bridges are also very close. Based on this observation, it is reasonable to assess the seismic vulnerability of any one bridge based on the known condition of another similar. This motivates us to find the correlation of seismic vulnerabilities between similar bridges.

However, the HAZUS model is just a static assessment of seismic risk; it only allows calculation of the failure probability for a single structure. To address this problem, here we adopt a post earthquake assessment system, based on the framework of Bensi et al. (2009) which can update the seismic probability of bridges after observing some evidence. In that work, the authors proposed a probabilistic Decision-Support System (DSS) for near-real time emergency response, after a seismic event, based on a Bayesian Network methodology. This DSS incorporates a wide-range of sources and provides a comprehensive description of the state of a geographically distributed infrastructure system.

In this paper, we apply the framework to the APT-BMS; twin bridges named Fersina-Canezza and Avisio are considered in this system. Here, by 'twin' bridges we mean that the two bridges have similar characteristics as to type, material and construction year. The basic idea is that when an earthquake occurs, the limit state of one bridge is detected or the information on earthquake magnitude is obtained, the distribution of other unobserved variables such as the probability of another bridge being in some damage state can be updated.

1.2 *Application of Bayesian Network in civil engineering risk assessment*

A Bayesian Network (BN) is a directed acyclic graph (traditionally abbreviated DAG) together with a set of nodes and a set of directed edges (Jensen & Nielsen 2007). The nodes represent variables and the edges represent condition relationships among

the variables. The BN originates from the field of artificial intelligence and incorporates graph theory and probability theory. It is a useful tool that helps perform uncertainty analysis in complex systems. For an extensive explanation of BN, see Jensen & Nielsen (2007). Due to their generality, such as incorporation of graph theory and probabilistic inference, accounting for the evolving nature of available information, BNs have been widely used in many areas in the last two decades.

However, the general BN algorithm can only effectively handle discrete variables, while most variables in civil engineering areas are continuous; therefore the application of BN to civil engineering is still at a preliminary stage. Friis-Hansen (2000) is one of the first publications that applied BN to engineering risk related issues: by solving decision problems in marine engineering, the potential of BNs in risk analysis was investigated and their advantages such as flexibility and compatibility were demonstrated; Nishijima et al. (2009) modelled a transportation system with BN which related the reliabilities of individual system components to overall performance: given an acceptance criteria, it proposed finding target reliabilities for components in a complex engineering system. Daniel Straub has done much work in applying BN to civil engineering risk assessment: first he proposed a framework for the earthquake hazard through a ground motion attenuation law, and then applied this model to a transportation system (Straub et al. 2008, Bensi et al. 2009). In addition, he also proposed some models to calculate the risks of rock-falls and avalanches, based on Bayesian updating (Straub 2005, Straub & Grêt 2006, Straub & Schubert 2008).

Most of the above research used discretization to approximate continuous variables when dealing with hybrid BNs, which contain both continuous and discrete variables. The continuous variables are replaced by discrete variables with a sufficient number of stages. However, this would add to the computation burden when high accuracy is to be achieved. Fortunately, when the continuous variables have conditional linear Gaussian distributions, and the discrete nodes do not have continuous parents, there exists exact inference in hybrid BNs (Lauritzen & Jensen 2001). In this paper, in order to avoid approximating continuous variables, all the variables in BN are assumed to follow Gaussian distributions, so the exact inference methods can be performed on the framework.

The remainder of the paper is as follows. In section 2, the HAUZUS, demand and capacity models are described. In section 3, the general computation scheme which includes construction of a junction tree, initialization and propagation, is introduced and performed on a case study. Last, the results are given and analyzed.

2 MODEL DESCRIPTION

2.1 Descriptions of the DSS

Bensi et al. (2009) modelled seismic demands of an infrastructure system by constructing a BN model of ground motion intensity. In that BN model, the seismic intensities (S_i), normally characterized as peak ground accelerations (PGA) at different sites across a spatially distributed infrastructure system following an earthquake, are expressed as a function of the magnitude (M), site-to-source distance (R_i), and other characteristics of the source and site (X_i), such as the type of faulting mechanism and the site shear-wave velocity; the source-to-site distance is a function of the earthquake location and magnitude.

Given the distribution of ground motion intensity at the site, the performance of infrastructure system components is modelled using fragility functions which provide the probability of exceeding some specific damage state. Then the system performance is modelled based on the performance of its components. Figure 1 gives the conceptual framework, taken from that paper.

In this paper, we apply this DSS to two twin bridges in APT-BMS. In order to facilitate computations, some simplifications and modifications are made to the framework in Bensi et al. (2009). Below we introduce the demand model, capacity model and fragility function in the application framework.

2.2 Bridges descriptions

The Fersina-Canezza (A) and Avisio (B) are 'twin' bridges in APT-BMS. Both are 3 span prestressed concrete bridges with wall piers, non monolithic abutments, built in year 1967. The lengths of the two bridges are 58.3m and 57.5m respectively. In figure 2 and figure 3 we can see overviews and cross sections of these structures.

2.3 Demand model

The attenuation relation for peak horizontal acceleration is as follows (Joyner & Boore 1981):

$$\log PGA = 0.249M - \log r - 0.00255r + 0.26E_s - 1.02$$

(1)

where PGA is peak ground acceleration in g; M is magnitude of earthquake in terms of the Richter scale; r is the source-to-site distance in km; E_s is the error term with a standard Gaussian distribution. In Bensi et al. (2009), M is assumed to follow truncated exponential distribution. To facilitate calculation, in this paper we assume it has Gaussian distribution.
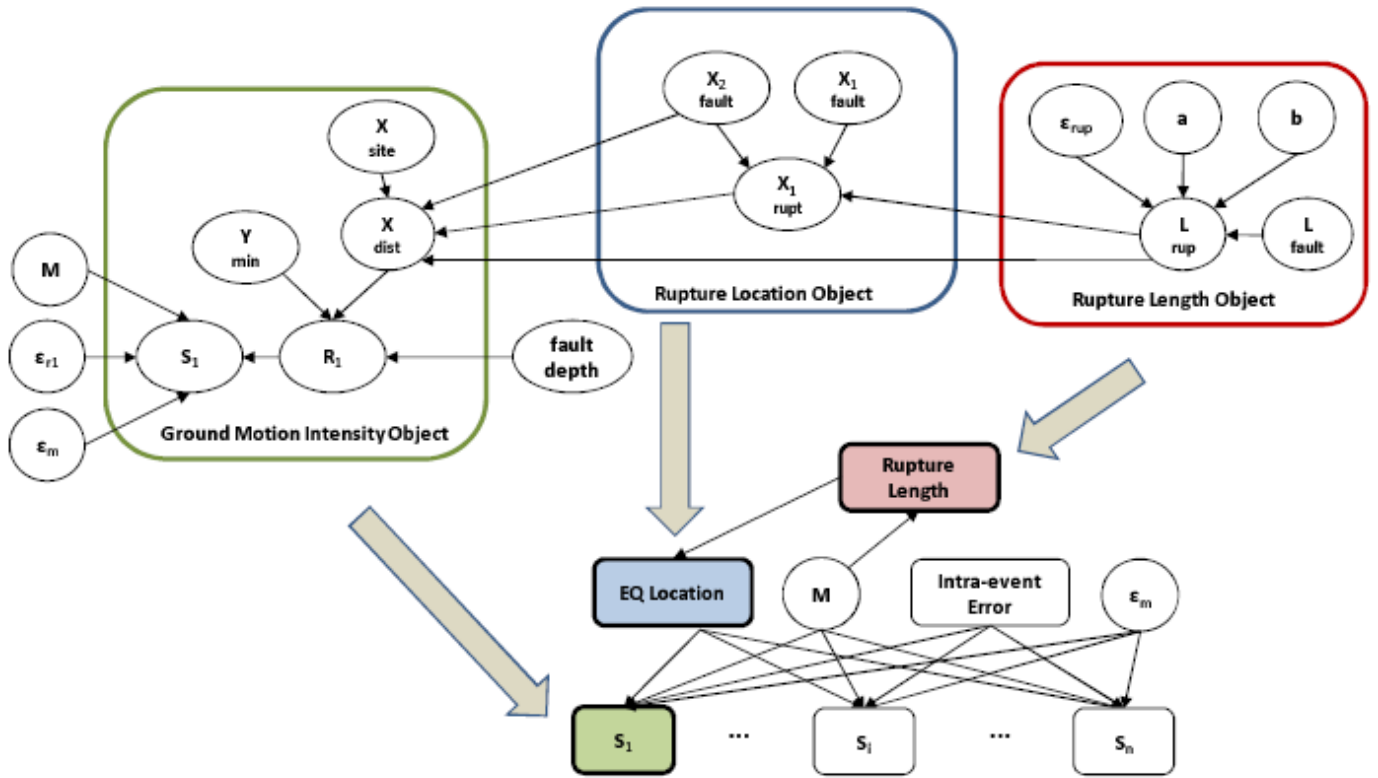
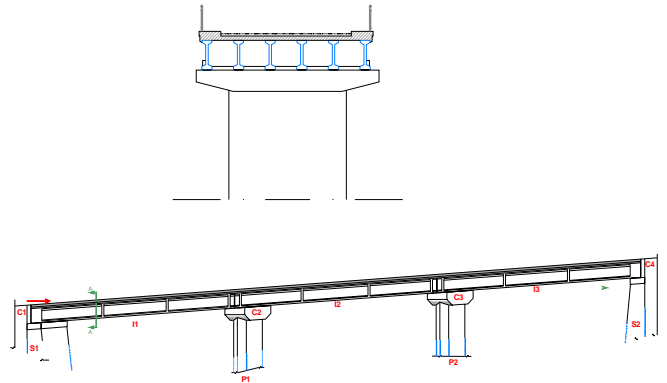Figure 1. Conceptual framework of BN in Bensi et al. (2009)

Figure 2. Bridge over the Fersina-Canezza (a) overview (b) elevation of piers and deck
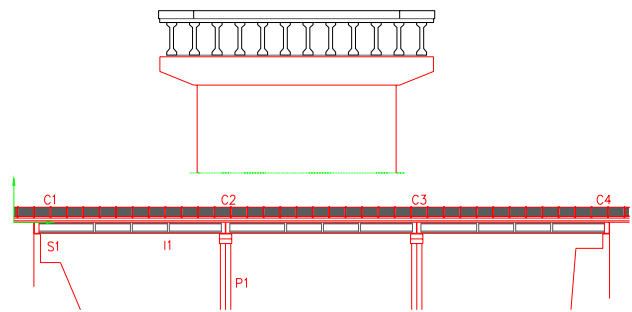

Figure 3. Bridge over Avisio (a) overview (b) elevation of the piers and deck

2.4 HAZUS model

Fragility curves are conditional probability statements which give the likelihood of a bridge reaching or exceeding a particular damage level for an earthquake of a given intensity (Shinozuka et al. 2000, Nielson 2005), this normally expressed as peak ground acceleration (PGA). The fragility function used in this paper is given by the HAZUS model (FEMA 2003). In this model, the probability of being in or exceeding a damage state is modelled as:

$$P_i = \Phi[\frac{1}{\beta}\ln(\frac{PGA}{A_i})] \quad i = 1,2,3,4 \tag{2}$$

where Φ is the standard log-normal cumulative distribution function; A_i is the median spectral acceleration that causes the ith damage level (operational, damage control, life safety, collapse); β is the normalized composite log-normal standard deviation which takes account of uncertainty and randomness for both capacity and demand. Basöz & Mander (1999) recommend that β=0.6. Although this value should be better tuned to take into account the uncertainties embedded separately, here for simplicity we acknowledge Basöz & Mander's suggestion.

2.5 *Capacity model*

Based on Yue et al. (2010), the median spectral acceleration A_i in equation (2) is calculated as:

$$A_i = \frac{2\pi}{S \cdot \eta \cdot F_0} \cdot \sqrt{\frac{C_C \cdot \Delta}{g} \cdot \frac{K_{3D}}{T_C}} \tag{3}$$

where C_c is the capacity factor; S is the coefficient that relates to the soil type; η is the damping correction factor with a reference value of η=1 for 5% viscous damping; F_0 is the spectral amplification factor; T_C is the upper limit of the period of the constant spectral acceleration branch; K_{3D} is a factor accounting for the 3D arching action when displacements are sufficiently large; Δ is maximum displacement response in meters, assumed as [0.05, 0.1, 0.175, 0.3] here.

In equation (3), all the parameters are deterministic except the capacity factor C_c.

Since the two bridges both have wall piers, their possible damage group belongs to the type "weak bearings with strong piers". According to Basöz & Mander (1999), the capacities are assumed to arise from bearings only. In this case, it is assumed that:

$$C_c = \mu_t \tag{4}$$

where μ_t=coefficient of sliding friction of the bearings in the transverse direction. The reader is referred to Yue et al. (2010) for further information.

In order to consider the relationship between different limit states, the friction coefficient for each limit state is assumed to have a linear relation with some factor f:

$$[(\mu_t)_1, (\mu_t)_2, (\mu_t)_3, (\mu_t)_4] = [0.85, 0.75, 0.75, 0.75] \cdot f \tag{5}$$

f is assumed to follow lognormal distribution.

$$\log f : N(0, 0.01) \tag{6}$$

An error term E_c is used to consider the uncertainty in the capacity model.

$$(C_c)_i = (\mu_t)_i \cdot e_c \tag{7}$$

In equation (7), the uncertainty term e_c is assumed to follow the distribution.

$$E_c = \log e_c : N(0, 0.0001) \tag{8}$$

Note that for different limit states, displacement responses Δ differ, so the the median spectral accelerations A_i in equation (3) are also different even though they have the same friction coefficient in equation (5).

2.6 *Calculation framework*

Figure 4 is the Bayesian network for the post-earthquake assessment framework. In this framework, M is the earthquake magnitude:

$$M : N(5, 0.25) \tag{9}$$

S_1 and S_2 are factors related to seismic intensities at the different sites where the two bridges are located:

$$S_1 = (\log PGA_a) \tag{10a}$$

$$S_2 = (\log PGA_b) \tag{10b}$$

The source-to-site distances for the two bridges are 10 and 20 respectively. E_{s1} and E_{s2} are factors related to intensity uncertainties; E_{c1} and E_{c2} are factors related to capacity uncertainties defined in equation (8); C is the factor that correlates the capacities of the two bridges:

$$C = \log f \tag{11}$$

OLS, DLS, LLS, and CLS are factors related to the probabilities of exceeding limit state operational, damage control, life safety, and collapse respectively. Since all the variables in this BN must follow Gaussian distribution, we use the variable ($lnPGA$-lnA_i)/ β rather than Φ(($lnPGA$-lnA_i)/ β) to represent the probability:

$$OLS = \frac{1}{\beta} \ln(\frac{PGA}{A_1}) \tag{12a}$$

$$DLS = \frac{1}{\beta} \ln(\frac{PGA}{A_2}) \tag{12b}$$

$$LLS = \frac{1}{\beta} \ln(\frac{PGA}{A_3}) \tag{12c}$$

$$CLS = \frac{1}{\beta} \ln(\frac{PGA}{A_4}) \tag{12d}$$

After discussion of the models embedded in the framework, the next section will give the general computation procedures in conditional Gaussian BN.
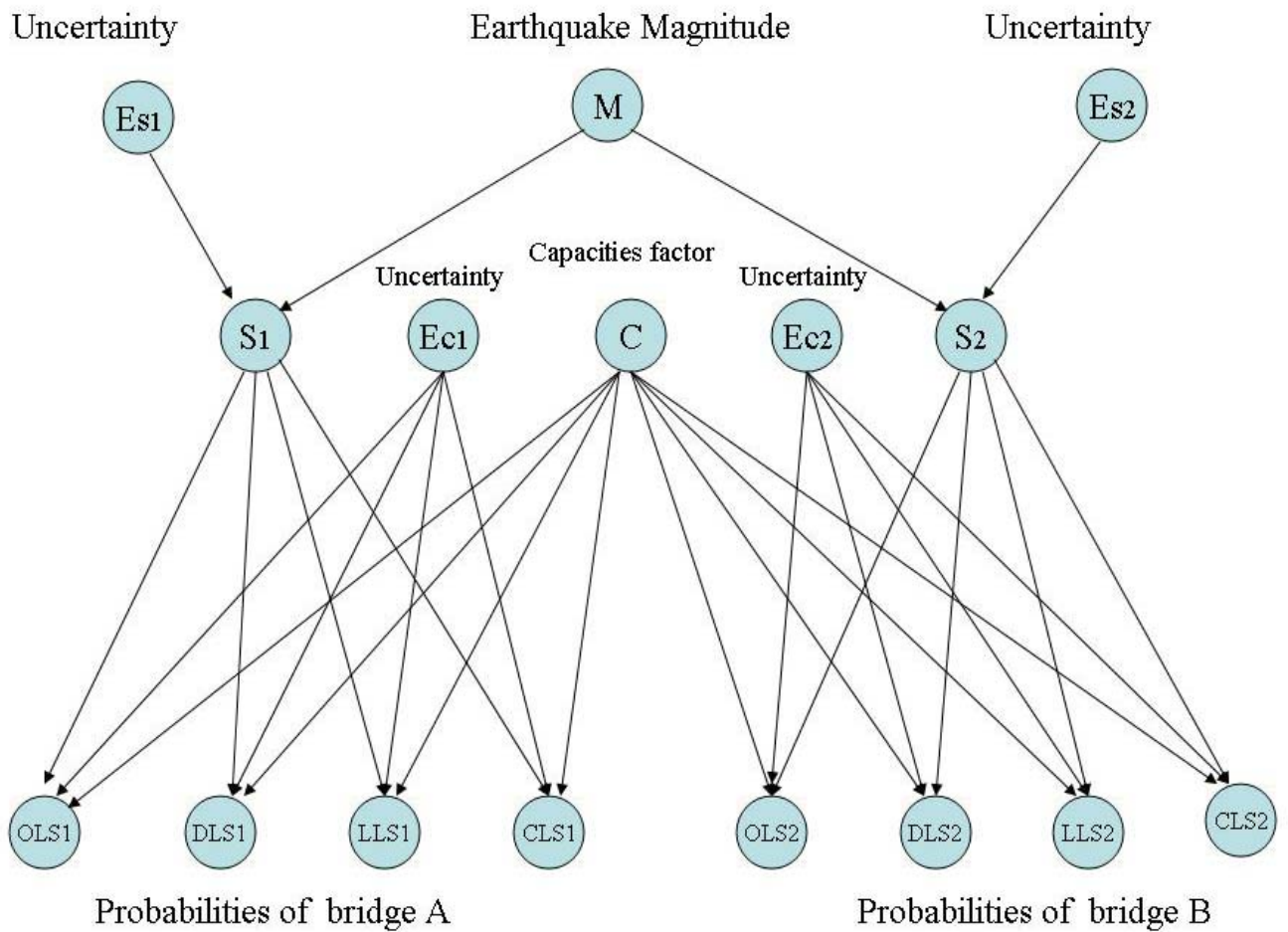
Figure 4. The Bayesian Network for the for the post-earthquake assessment framework
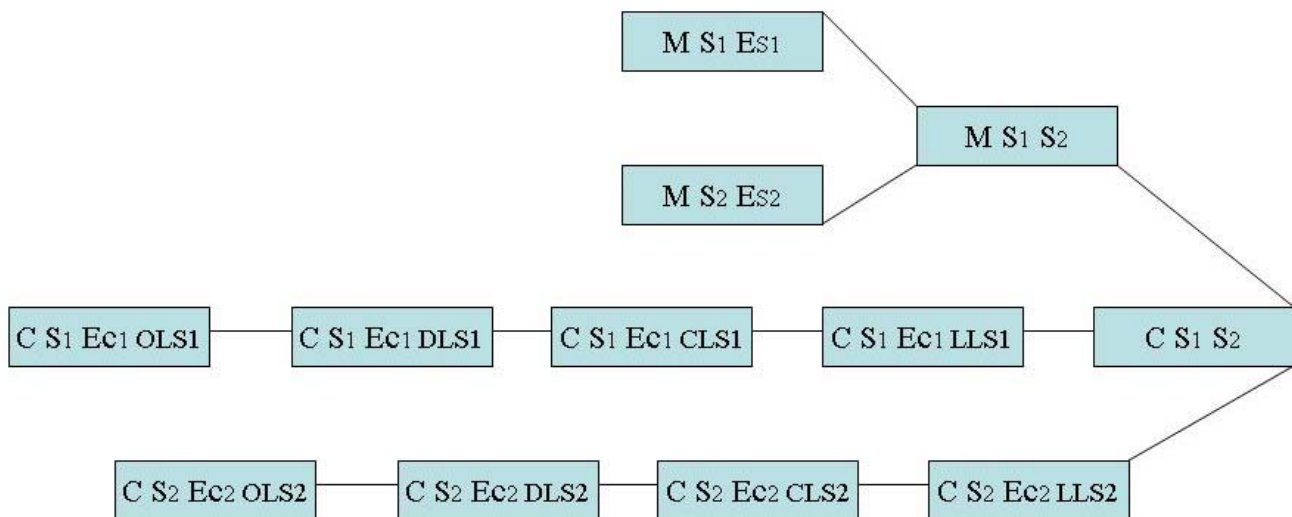

Figure 5. The junction tree structure for the BN in fig 4.

3 BAYESIAN NETWORK COMPUTATION

The previous section introduced the conceptual framework and the initial assumptions as to the relevant variables. In this section, we show the general computation procedures including: the construction of a junction tree, initialization, entering evidence and local computation, and then the framework is calculated using HUGIN software (http://www.hugin.com).

A junction tree is a tree structure for analysing decision problems. Given a directed acyclic graph, the basic steps to construct a junction tree are as follows (Jensen & Nielsen 2007):

1. Moralisation. Marry parents with common children and drop directions on the arcs.
2. Triangulation. Set an elimination sequence and form a triangulated graph. A clique is formed

from the eliminated variable and its remaining neighbours. If all variables of one clique belong to an existing clique, then it is not a clique. This is the key part in the junction tree construction, because it governs the size of cliques and efficiency of the computations.

3. Join the cliques H_1, H_2, H_3, …, H_k to form a tree which has the running-intersection property. The running-intersection property means that the elements of the intersection set of H_1 and H_k must be included in all the cliques H_2, H_3 , …, H_{k-1} that between H_1 and H_k.

Once the junction tree has been established, all the potentials which give the conditional relationship between variables are assigned to the cliques. For each variable x, if one clique contains x and $pa(x)$ which means parents of x, then the potential $P(x|pa(x))$ is assigned to it. After the initialization, all inference and updating operations are performed on the clique tables.

The propagation operation includes two parts: collect evidence and distribute evidence. Collecting evidence involves sending messages from the leaves of the junction tree to the root. A clique is allowed to send a message if it is a leaf or if it has received messages from all of its neighbours that are further away from the root. Distributing evidence involves sending message from the root to all other cliques. A clique is allowed to send a message if it has received one from its neighbour closer to the root (Cowell 2005).

Once evidence collection (Fig. 6) and distribution (Fig. 7) are completed, the posterior distributions can be obtained through marginalization and combination.
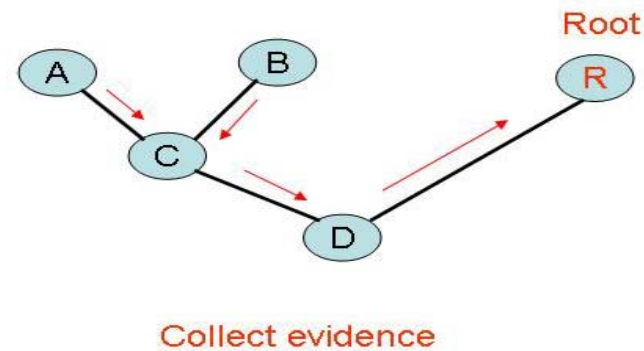

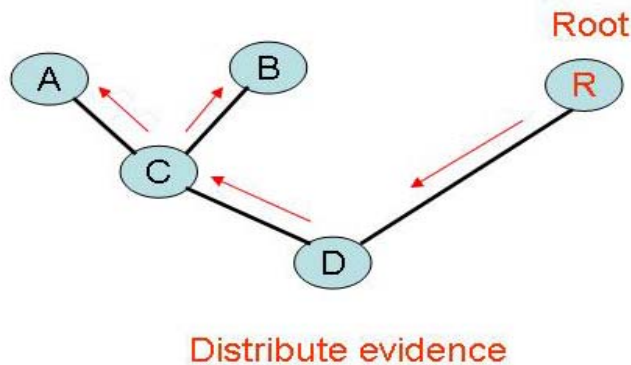Figure 6. The procedure for collecting evidence

Figure 7. The procedure for distributing evidence

4 RESULTS

Table 1.The initial results without evidence

Parameter	Mean	Variation	Corresponding variable	Corresponding value
S1	-0.8	0.08	PGA	1.58×10^{-1}
S2	-1.13	0.08	PGA	7.41×10^{-2}
OLS1	-2.77	1.26	P_{a1}	2.80×10^{-3}
DLS1	-3.25	1.26	P_{a2}	5.77×10^{-4}
LLS1	-3.71	1.26	P_{a3}	1.04×10^{-4}
CLS1	-4.16	1.26	P_{a4}	1.59×10^{-5}
OLS2	-4.13	1.26	P_{b1}	1.81×10^{-5}
DLS2	-4.60	1.26	P_{b2}	2.11×10^{-6}
LLS2	-5.07	1.26	P_{b3}	1.99×10^{-7}
CLS2	-5.52	1.26	P_{b4}	1.70×10^{-8}

Table 2.The updated results given evidence OLS2=2

Parameter	Mean	Variation	Corresponding variable	Corresponding value
M	6.16	0.20	M	6.16
S1	-0.51	0.08	PGA	3.09×10^{-1}
S2	0.42	2.45×10^{-3}	PGA	2.63
OLS1	-1.49	1.21	P_{a1}	6.81×10^{-2}
DLS1	-1.96	1.21	P_{a2}	2.50×10^{-2}
LLS1	-2.43	1.21	P_{a3}	7.50×10^{-3}
CLS1	-2.88	1.21	P_{a4}	2.00×10^{-3}
OLS2	2	0	P_{b1}	1
DLS2	1.53	0	P_{b2}	9.37×10^{-1}
LLS2	1.06	0	P_{b3}	8.55×10^{-1}
CLS2	0.61	0	P_{b4}	7.29×10^{-1}

First, suppose no evidence is observed, the initial distributions of variables are shown in table 1.

Table 1 gives the mean value and variation for the conceptual parameters in the framework, and then the conceptual parameters are converted into the physical variables. For example, the parameter $S1$ in the framework means the logarithmic value of PGA in bridge A, so the value of the corresponding variable is: PGA=10^{S1}=$10^{-0.8}$=0.1585g.

So the initial probabilities of bridge A exceeding the various limit states are: $\Phi(-2.77) = 2.80 \times 10^{-3}$ for operational limit state; $\Phi(-3.25) = 5.77 \times 10^{-4}$ for damage control limit state; $\Phi(-3.71) = 1.04 \times 10^{-4}$ for life safety limit state; $\Phi(-4.16) = 1.59 \times 10^{-5}$ for collapse limit state.

Suppose that bridge B is observed to exceed the operational limit state. Because in this framework we use $\Phi(OLS2)$ as the probability of bridge B exceeding the operational limit state, $\Phi(OLS2)$=1. Since $\Phi(2)$ =0.9772, we can use value 2 as the evidence value of $OLS2$. The results are given in table 2. After given evidence OLS=2, the updated probability of bridge A exceeding the various limit states are: $\Phi(-1.49) = 6.81 \times 10^{-2}$ for operational limit state; $\Phi(-1.96) = 2.50 \times 10^{-2}$ for damage control limit state; $\Phi(-2.43) = 7.50 \times 10^{-3}$ for life safety limit state; $\Phi(-2.88) = 2.00 \times 10^{-3}$ for collapse limit state.

From table 2, we can see that after observing bridge B reaching the operational limit state, the probability that bridge *A* exceeds the operational limit state has increased from 0.0028 to 0.0681. The mean value of magnitude *M* has increased from 5.00 to 6.16, so the earthquake is expected to be of larger magnitude than the original assumption; and the seismic intensities at bridges *A* and *B* are expected to be 0.309g and 2.63g, larger than the original values 0.1585g and 0.0741g.

5 CONCLUSIONS AND FUTURE WORK

A framework for seismic vulnerability assessment is introduced. Given the seismic probability of one bridge, this framework can update the probability of another similar bridge. The results can be used for post-earthquake decisions.

However, it is important to keep in mind the limits of this framework. The first is related to the capacity model. In this paper, the capacity is assumed to arise from the bridge bearings. When the bridges are seated on strong bearings with weak piers, the capacity is assumed that of the piers. In this case, the capacity model will be more complex. Also, the variation of capacity factor must be based on empirical data. The second limit is the limitation of the computation scheme used in this paper; it can only deal with conditional Gaussian Bayesian networks, where all the continuous variables must follow Gaussian distribution and the discrete variables cannot have continuous parents. The last limitation is the distribution of magnitude. In this paper, the moment magnitude *M* is assumed to follow normal distribution, which may cause error in reality. In Kang et al. (2008), *M* is assumed to follow a truncated exponential distribution. We acknowledge that the truncated exponential distribution is more reasonable, but we assume Gaussian distribution for computation purposes.

Before applying the framework to reality, there are several issues that need to be addressed. These include:

(1) A computation scheme that has no restriction on the construction of BN is required. In the computation scheme used in this paper, all the variables must follow Gaussian distribution and discrete variables cannot have continuous parents. These two constraints limit the framework construction. Once these constrains are removed, the variable *OLS1* can be replaced directly with a discrete variable which has two states: bridge *A* exceeds the operational level and bridge A does not.

(2) A more refined framework is required. In this paper, only two bridges are considered. In the next step, we will generate a more sophisticated model including the response of all the elements within the roadway network, such as roads, tunnels and retaining walls.

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