Bayesian Network Framework for Macro-Scale Seismic Risk Assessment and Decision Making For Bridges

S. Broglio
ROSE Programme, UME School, IUSS Pavia, Italy

H. Crowley
EUCENTRE, Pavia, Italy

R. Pinho
Civil Engineering and Architectural Dept., University of Pavia, Italy

SUMMARY:
An efficient post-event assessment of bridges immediately after an earthquake can be useful in the organization of the initial emergency phase. The information available shortly after an earthquake can be difficult to manage: it may be in continuous evolution and arriving from different sources (e.g. sensors placed on the structure, seismological sources and recordings of the ground motion). This large amount of data can be processed to assess the condition of the structures and used to make decisions about its operation through the use of Bayesian Network (BN) models. Such tools allow probabilistic updating of the state of the structure in light of any observed evidence. This information, together with estimated losses relative to different bridge damage levels, is then used to formulate a decision problem regarding the optimal decision to make. An example presented herein will demonstrate the methodology for a bridge in a macro-scale analysis context.

Keywords: Bayesian Networks, bridge, decision making, risk assessment

1. INTRODUCTION

In the aftermath of an earthquake, it is useful to know the general condition of an entire area, though it is generally not possible to assess every single structure in detail. For this reason, macro-scale analyses are important to receive preliminary information about the most likely condition of the structures in a given area.

This study focuses on bridges. Bridges can be considered as strategic elements of civil transportation infrastructures that guarantee connection between different parts of the urban grid, linking together different kinds of communities and businesses. Assessment of whether the connection is still working after an extreme event (e.g. an earthquake, a hurricane, an explosion) can be very important in the emergency phase organization. In order to be able to make such an assessment quickly and efficiently, in this work, the traditional macro-scale analysis approach is integrated into a flexible Bayesian Network (BN) framework as a suitable modelling tool for complex systems able to merge different kinds of knowledge (objective and subjective) leading to a prediction (and diagnosis) of the state of a structure.

An example is shown in this paper demonstrating the possibility to use this tool for seismic risk assessment and decision making.

2. BNs AS SUITABLE TOOLS FOR SEISMIC RISK ASSESSMENT

The use of BNs as risk assessment tools is mainly based on their capability to merge different kinds of information and knowledge together with their intuitive graphical communication language which is helpful when different parts are involved in a decision phase.

BNs are made of nodes (i.e. variables) and arrows (i.e. links indicating the relationships between variables). Provided the nodes representing specific variables are present in the network, they can be updated using any kind of information (e.g. from seismological sources, from transducers, with subjective information coming from visual inspection of the structure).

Furthermore, information can propagate in a BN both forwards and backwards. This is because the probabilistic inference in BNs can be both predictive and diagnostic. This property represents the power of this tool because in structural assessment, it is important to be able to update the scenario with the information coming from different sources.

In addition, BNs are becoming a common language in the engineering community. An important sign is given by the fact that, from 2001 to 2008 the number of relevant publications in this field per year has increased from about 4 to 18 (Weber *et al.*, 2012) (Fig. 2.1)

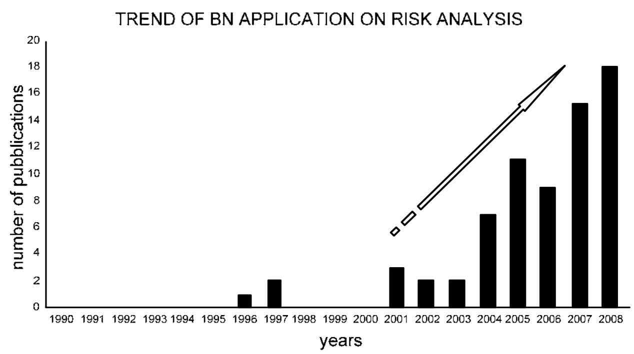


Figure 2.1. Increasing use of BN in risk analysis (Weber *et al*. 2012)

3. WHAT ARE BNs? A BRIEF BACKGROUND

Bayesian Networks are a set of random variables linked together defining a so-called Direct Acyclic Graph (DAG) (Fig. 3.2).

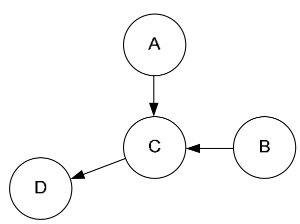


Figure 3.2. Simple DAG

Each variable is characterized by a Probability Mass Function (PMF). This is *marginal*, if the node is a root node (i.e. without preceding inks), or *conditional* if the node is conditional upon the other nodes. In Fig. 3.2, for instance, Nodes A and B are characterized by a marginal PMF and they are called *parents* of C (that is a *child* of A and B), given in terms of conditional PMF.

Each node is discretized into a set of mutually exclusive, statistically independent states and it is associated with a Conditional Probability Table (CPT) representing the conditional probability of occurrence of that variable, given its parent nodes. For example, the CPT of the variable C is given by Eqn. 3.1.

$$P(C \mid A,B) = P(C \mid pa(C)) \quad (3.1)$$

where *P* indicates the probability and *pa(C)* indicates the parents node of *C*.

As mentioned earlier, BNs can be updated with any available information and they are suitable for answering probabilistic queries when one or more variables are observed. For instance, take the variable A which is subdivided in *n* mutually exclusive states (i.e. $a_1, a_2,.., a_n$). Let $e=\{A=a_1\}$ denote the observed information or evidence on the variable.

The conditional distribution of any other set of the variables given this evidence is obtained by applying the Bayes' rule. For example, the updated joint distribution of random variables *B* and *C* given *a* is given in Eqn. 3.3.

$$P(B,C \mid A=a_1)=\frac{P(A,B,C)}{P(A=a_1)} \tag{3.3}$$

Other kinds of nodes can be used in the definition of a BN: decision nodes and value nodes. The former account for all the possible outcomes considered in the decision phase, the latter assign a value to each option. The use of all these nodes is presented in this paper.

4. BN FRAMEWORK DESCRIPTION

The BN framework proposed in this paper has been developed for macro-scale seismic risk assessment and decision making for bridges. In the definition of this framework, different tools have been involved. Structural analyses, traditional probabilistic concepts and macro-scale analysis tools are coordinated through the BN philosophy. The proposed BN framework (Fig. 4.1) is schematized using three sub-models.

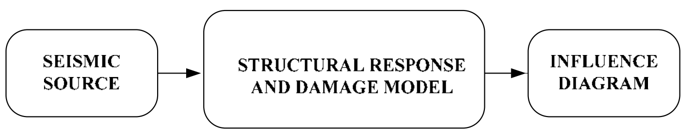


Figure 4.1. Proposed BN Framework

Details relative to the aforementioned sub-models are given in the following sections.

4.1 Seismic Source Sub-model

The Seismic Source sub-model presented herein, has been developed for a 3D plane source and the relationships between the variables are mainly defined through geometrical considerations.

The already mentioned sub-model is given in Fig. 4.2 where X_h and Y_h are the hypocentre position coordinates, X_{Pf} and Y_{Pf} are the coordinates of a selected reference point of the rupture (P_{ref} is given Fig. 4.3), *A* is the rupture area, *M* is the magnitude of the event, Z_{tor}, R_{jb} and R_{rup} are the ground motion parameters representing the seismogenetic depth, the Joyner-Boore distance and the rupture distance respectively, E_{jb-rup} is the model error used for the definition of R_{rup} given as a function of R_{jb} (details provided later) and *IM* is the considered Intensity Measure.

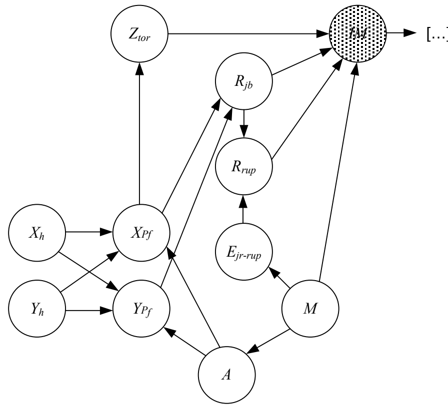


Figure 4.2. BN framework for seismic 3D plane source

To establish the relationships between variables in the BN-based seismic source model, some assumptions have been followed. The hypocentre position is randomly simulated on the fault assuming that all the points of the surface are equally likely (i.e. prior PMF for X_h and Y_h is uniform). Magnitude is simulated as truncated exponential as proposed by the modified Gutenberg-Richter model (Guttenberg and Richter, 1944). The rupture area A is defined as a function of magnitude (M) following the relationship proposed by Wells and Coppersmith (1994) and given in Eqn. 4.4:

$$log_{10}(A) = -2.87 + 0.82 \cdot M + \varepsilon \cdot 0.22 \tag{4.4}$$

where ε is assumed to be standard normal.

Considering that the position of the hypocentre can be anywhere on the fault and that the rupture area is assumed square, it is possible that the simulated area is too big to fall entirely in the fault plane. For this study, the theory of the conservation of the area is assumed as valid and the rupture is shifted inside the fault as shown in Fig. 4.3.

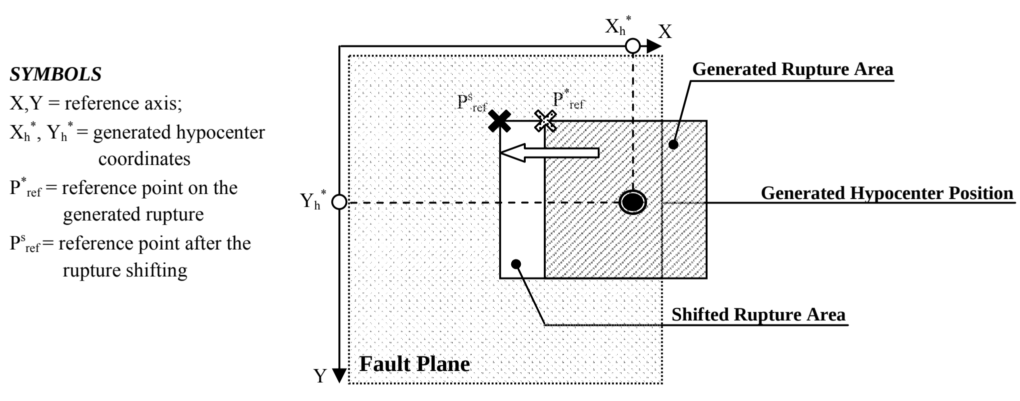


Figure 4.3. Hypocentre position close to the fault boundary

Once the position and the dimension of the rupture area are defined, the parameters for the definition of the intensity measure are determined through geometrical considerations.

The Joyner-Boore distance is defined adopting an auxiliary variable (Y_{ref}) as illustrated in Fig. 4.4. Additional details about the formal definition of these parameters can be found in Broglio (2011).

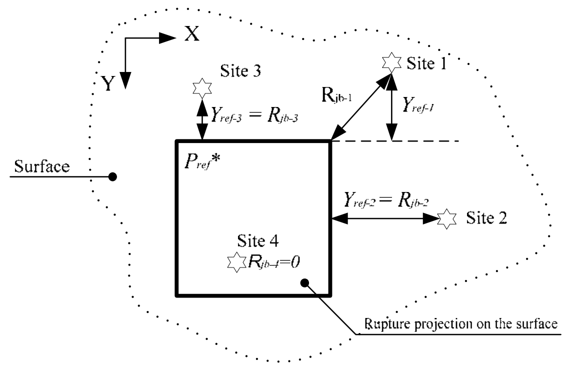


Figure 4.4. Geometrical Definition of R_{jb}

The rupture distance has been defined through empirical relationships as specified in Scherbaum *et al*. (2004). The seismogenetic depth (Z_{tor}) has been defined as a function of the geometry of the fault. R_{jb}, R_{rup}, Z_{tor} and M are then used for the simulation of the IM CPT.

4.2 Structural Response and Damage Sub-model

The Structural Response and Damage Sub-model is responsible for controlling the probabilistic relationships between the seismic event, the response of the structure and the consequent physical damage.

The continuity between the Seismic Source Sub-model and the Structural Response and Damage Sub-model is given by the *IM*. This is a Structure-Dependent Displacement-Based IM (details relative to its definition and selection can be found Broglio *et al.* (2010) and Broglio (2011)). As can be noted (Fig. 4.2 and Fig. 4.5), the *IM* is defined in terms of both ground motion parameters and structural properties, such as T_y (i.e. the period of the bridge) defined as a function D_L (i.e. deck length) and Δ_y (i.e. yield displacement of the bridge).

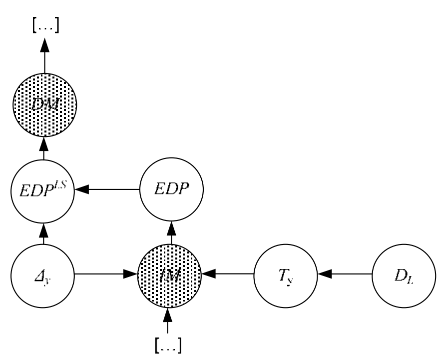


Figure 4.5. Structural Response and Damage Sub-model

The definition of the structural properties, the relationship and the predictive laws linking the *IM* to the *EDP* (i.e. Engineering Demand Parameter), have been defined by performing a parametric investigation on a population of 21 concrete continuum deck, regular and irregular bridges, with seven different pier layouts (the length of the pier is 7m, 14m and 21m, labelled 1,2 and 3 respectively), two deck lengths (i.e. 200m and 400m) and three different abutment types accounting for different behaviours (indicated as A, B and C).

The predictive relationship between IM and EDP is given by Eqn.4.6 (derived from Cornell *et al.* (2002), where the parameters a, b (regression parameters) and β (dispersion) are assessed using linear regression analysis between the two variables and ε is assumed to be standard normal). In this study, EDP represents the maximum mean displacement and it is obtained performing nonlinear dynamic analysis by applying a group of accelerograms to each bridge of the population.

$$log(EDP) = b\,log(IM) + log(a) + \varepsilon\beta \qquad (4.6)$$

Relationships between different structural properties are defined by performing pseudo-static analyses (in particular Displacement-Based Adaptive Pushover, DAP). Details about this approximate formulation are given in Broglio (2011).

The node EDP^{LS} represents the limit state given in terms of global displacement. This limits states are given in terms of system ductility, following the recommendations given by Priestley *et al*. (1996).

The variable *DM* accounts for the physical damage and it is defined through a likelihood matrix that specifies the probability to observe a particular physical damage in the structure given an observed level of displacement, as schematized in Table 4.1. The construction of this matrix is based on common sense and updating based on real data is desirable in future developments of this study.

Table 4.1. Example of the structure for the likelihood matrix

	LEVEL OF DISPLACEMENT (EDP^{LS})
PHYSICAL DAMAGE (DM)	Probability to observe a specific physical damage if the structure is performing at a given level of displacement.

4.3 Loss model and Influence Diagram

The BN can be used to support decision-making under uncertainty to define the optimal decision to make after a seismic event. The tool used to solve the decision problem is called the Influence Diagram (ID), which is a BN extended by the addition of decision and utility nodes. Each decision node has states indicating the available alternatives. Each of these alternatives is related to direct and indirect losses. Direct losses are those related to the damage of the building itself, while indirect losses are due to business slow-down if the bridge is closed, and the cost of liability if the bridge is left open, depending on the damage state of the bridge. Losses are represented by utility nodes. For this example, the total cost of direct and indirect losses is considered in an approximate way as normalized values (weights) relative to the cost replacement of the bridge.

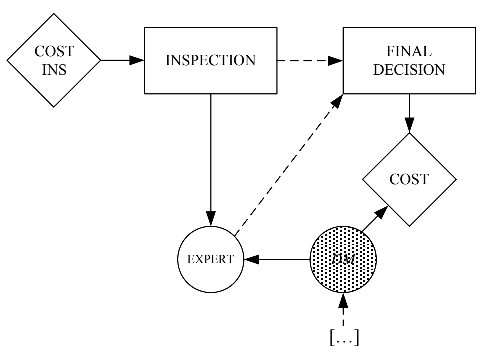


Figure 4.6. Influence Diagram (ID)

The Influence diagram used in this study is given in Fig. 4.6. This is composed by two decision nodes. These are INSPECTION (conduct or not conduct an inspection) and FINAL DECISION (continue operation, partial operation or close the bridge). These nodes are related to utility nodes, shown as diamonds. These nodes state the costs associated with each decision alternative (COST INSP is the cost of inspection and COST is the total cost related to closure, partial closure or non-closure of the bridge). The DM chance node represents the link between this sub-model and the Structural Response and Demand Sub-model, the EXPERT node indicates the quality of the inspection and is defined through the test-likelihood matrix. The additional information obtained by performing the inspection updates the probability distribution of the state of the bridge and, thus, influences the final decision.

5. EXAMPLE APPLICATION

This example has been developed to show the BNs application in the seismic risk assessment context, highlighting the use of the ID as an important tool for the decision making phase.

The source model applied in this example is the one presented in section 4.1 with reference to the rectangular plane fault shown in Fig. 5.1, recalling that the rupture area due to a seismic event is assumed to be square. Assuming that the plane source considered in this example is the simplified representation of the Paganica Fault, the dip angle is taken equal to 50°. The total area of the fault is then about 224km^2.

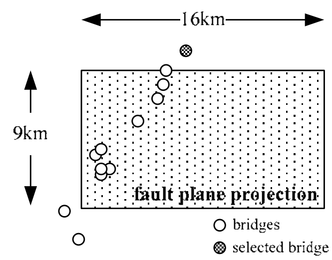


Figure 5.1. Fault and bridge population scheme

The structure properties are given by the deck length (D_L), the yield period (T_y) and the yield displacement (Δ_y) simulated following approximated relationships developed using the aforementioned bridge population. The structural response is given by the *EDP*. EDP^{LS} and *DM* are the variables relative representing the limit states and the physical damage states observed in the structure.

The EXPERT node gives the PMF of the possible inspection outcome, given the real (coming from the analyses) damage state. The COST INSP and the COST nodes are value nodes accounting for the values related to all the possible outcomes presented in the network and listed in the decision nodes (i.e. INSPECTION and FINAL DECISION).

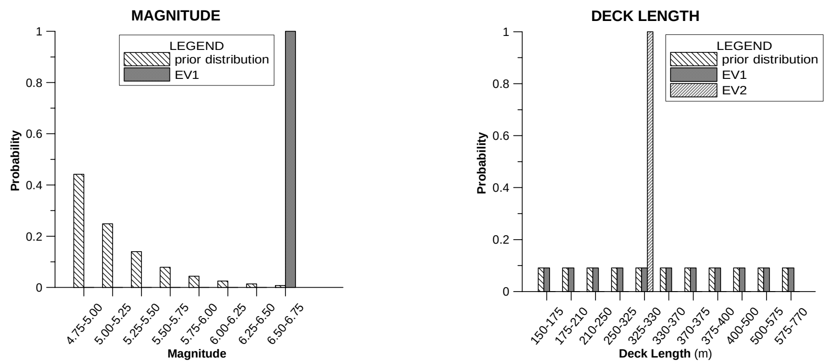
It is assumed that the evidence sequence given in Table 5.1 becomes available after an earthquake and the evolution of the variables involved is then observed each time an evidence is entered in the network.

Table 5.1. Evidence Sequence

Evidence 1	Magnitude [6.5-6.75]
Evidence 2	Deck Length [325 330] m
Evidence 3	Rupture Area [157 179] km^2
Evidence 4	EDP [0.15 0.15] m
Evidence 5	Expert Opinion [SPLITTING]

As can be seen in Fig. 5.2, as expected, the information about the magnitude does not influence the prior PMF relative to the deck length of the bridge under observation. The effect of Evidence 1 is clear in the Rupture Area PMF, shifting towards the right direction, thus showing higher probabilities for a larger rupture area than the one expected in the prior scenario (Fig. 5.3). As can be seen, the highest probability of occurrence is observed for the range [224.020 224.024] km^2 (given in Fig. 5.3 as

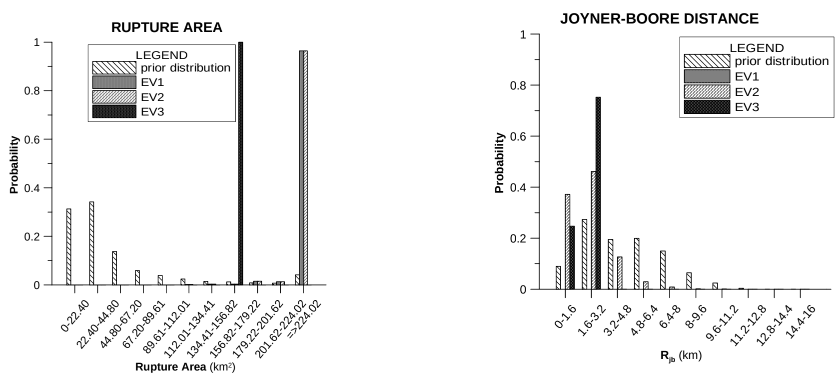
[224.020 ∞)). This is reasonable considering that the Wells and Coppersmith (1994) relationship has been used and the error has been simulated as normally distributed and truncated at +/-3σ.



(a) **(b)**

Figure 5.2. Magnitude and Deck length PMFs (prior and posterior)

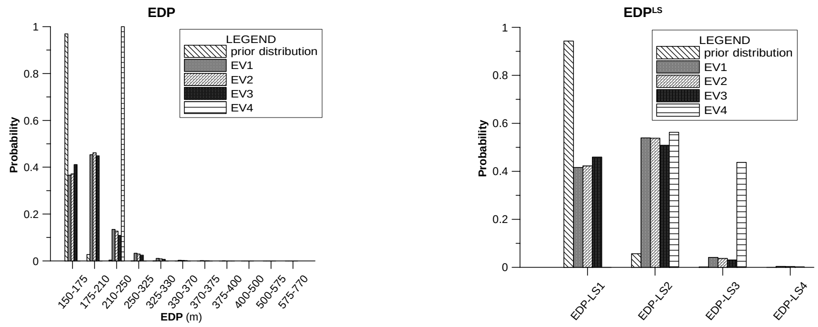
After the Evidence 1, the PMF relative to the *EDP* is shifted in the direction of higher displacement values than those observed as from the prior results (Fig. 5.4 (a)), and the EDP^{LS} PMF undergoes the same effect as the aforementioned variables (Fig. 5.4 (b)). *EDP* PMF, when Evidence 3 is entered in the network, shows a reduction of probability of occurrence in the [0.05 0.10] m state and an increasing of probability of occurrence in correspondence of the state [0 0.05] m, indicating that the PMF is moving slightly back. This can be explained by observing the evolution of the PMF relative to the Joyner-Boore distance when Evidence 2 and Evidence 3 are entered in the network (Fig. 5.3 (b)).



(a) **(b)**

Figure 5.3. Rupture Area and Joyner-Boore distance PMF (prior and posterior)

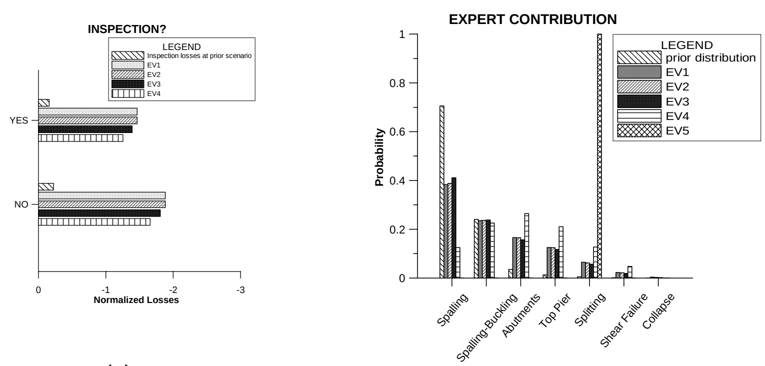
When Evidence 2 becomes available, the probability to have R_{jb} in the interval [0-1.6] km is about 44% and the probability to be in the next interval (i.e. [1.6 3.2] km) is 57%, with negligible probability to be in the interval [3.2 4.8] km. When information about the rupture area is introduced in the BN (Evidence 3), the probability to be in the [0-1.6] km interval decreases to 25%, and the probability relative to the next interval rises to 75%. The higher probability in the second R_{jb} state, with respect to the probability observed in Evidence 2, leads to a decreasing of probability of occurrence for the state [0.05 0.10] m of *EDP* from 46% to 44% for Evidence 3 and an increasing probability in the [0 0.05] m state, from 37% to 41%. As expected, the same effect can be observed in EDP^{LS}.



(a) **(b)**

Figure 5.4. Engineering Demand Parameter and relative limit states PMFs (prior and posterior)

At each evidence case, the INSPECTION node can be observed (Fig. 5.5). This node provides the results in terms of losses (e.g. normalized monetary losses) associated to both the real damage state of the structure and the decision to perform or not the inspection before the final decision. As can be seen in Fig. 5.5(a), the decision to inspect the bridge, before establishing the final decision, is preferred because it leads to lower loss than the opposite alternative. The optimal decision provided by the network is followed: and the decision-maker decides to inspect the bridge. At this point, the PMF of the possible answer of the expert is given based on the PMF relative to the real damage state of the bridge and the nature of the expert. The EXPERT node is defined as a function using a test-likelihood matrix relative to the confidence of the test relative to the inspector that is going to verify the bridge damage condition. The results obtained in this example are given in Fig. 5.5 (b).



(a) **(b)**

Figure 5.5. Losses relative to inspection and EXPERT PMF (prior and posterior)

As a final step, it is assumed that the information is received that the vertical elements show concrete splitting failure (Evidence 5). The results for the final decision in terms of losses (Operative?, Partially Operative?, Inoperative?) are then provided by the BN and shown in Fig. 5.6.

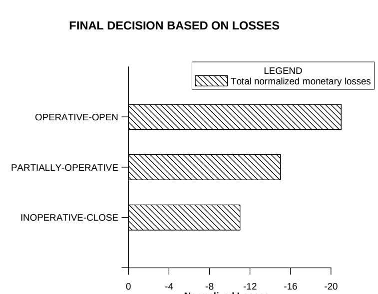


Figure 5.6. Evaluation of losses for the definition of final/optima decision

The final decision is based on direct and indirect losses related to the possible decision that the decision maker can make in the decision phase. As can be seen, the optimal decision for the example proposed herein is to close the bridge, yielding reduced losses when compared with the other options.

6. CONCLUSIONS

The BN methodology is an intuitive and valid tool for the management of the risk in the immediate aftermath of an earthquake because of its capability to be updated with different kinds of information, in any direction. In addition, BNs can be both predictive and diagnostic. Furthermore, the use of a graphic language, leads to an easy communication between the analyst and the decision-maker.

In the future many other aspects in the BN context can be included and investigated. For instance, in the definition of the proposed BN framework, a BN-based seismic source model is introduced. This model is based on some assumptions useful for the construction of the network. The proposed assumptions can be modified and improved in future development of the framework, such as with the inclusion of the directivity.

In terms of improving the BN framework, it would be possible to introduce the effect of aftershocks on the monitored structures. This additional step includes the definition of predictive relationships for the definition of the response of structures already damaged by the main shock and subjected to subsequent aftershocks.

In future developments, it will be useful to integrate the proposed BN framework with other applications able to automatically introduce the external information into the network. This information can be derived from accelerometers, transducers and health monitoring sensors placed on the structure. In addition applications producing graphs and prioritizing lists can be useful for practice as proposed in Bensi (2010).

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