Bayesian updating for rapid earthquake loss assessment of road network systems

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Abstract: Within moments following an earthquake event, observations collected from the affected area can be used to define a picture of expected losses and to provide emergency services with accurate information. A Bayesian Network framework could be used to update the prior loss estimates based on ground-motion prediction equations and fragility curves, considering various field observations (i.e., evidence). The present study explores the applicability of approximate Bayesian inference, based on Monte-Carlo Markov-Chain sampling algorithms, to a real-world network of roads where expected loss metrics pertain to the accessibility between damaged areas and hospitals in the region. Observations are gathered either from free-field stations (for updating the ground-motion field) or from structure-mounted stations (for the updating of the damage states of infrastructure components). It is found that the proposed Bayesian approach is able to process a system comprising hundreds of components with reasonable accuracy, time and computation cost. Emergency managers may readily use the updated loss distributions to make informed decisions.

Keywords: Bayesian inference; critical infrastructure; seismic risk; loss updating; road network

1. Introduction

Several rapid response systems have been developed worldwide, as detailed in the review by Guérin-Marthe et al. (2021). While such systems are mostly applied to common buildings and the estimation of casualties, the treatment of the performance loss of critical infrastructure and its consequences remains mostly overlooked. A rigorous rapid response system should ensure the propagation of the uncertainties due to the estimation of ground shaking up to loss predictions. Therefore, this paper investigates a proof-of-concept rapid response procedure that would integrate the following features, in answer to the aforementioned gaps: *(1)* loss estimation for built areas and infrastructure systems, *(2)* integration of various types of observations to constrain the predictions, *(3)* propagation of all sources of uncertainty, from hazard to losses, and (4) ability to treat real-world systems over large areas.

Bayesian Networks (BNs) have emerged as a very promising mathematical tool, well adapted to seismic risk analyses that mobilize a probabilistic framework and dependencies between many variables (Bensi et al., 2013). The inference operations on a BN enable the combination of the initial estimates (i.e., prior distribution provided by predictive models) and of field observations (i.e., providing evidence at some nodes) in order to generate updated posterior distributions of the variables of interest. Therefore, thanks to their probabilistic inference capabilities, BNs constitute an adequate solution for the updating of damage and loss estimates in the crisis phase (Bensi et al., 2015). While many previous studies have investigated the scalability issues of BNs (Tien et al., 2016; Gehl et al., 2018; Byun et al., 2019), their actual application to large real-world systems remains a challenge when considering the spatial distribution of the ground-motion field.

Pending further developments of BN algorithms that are able to address some of the scalability issues, it is proposed here to adopt a more pragmatic approach based on a sampling inference algorithm (i.e., Monte-Carlo Markov-Chain sampling). The objective is to exploit state-of-the-art techniques in order to demonstrate the use of BNs in an operational capacity during the rapid response phase (see Figure 1).

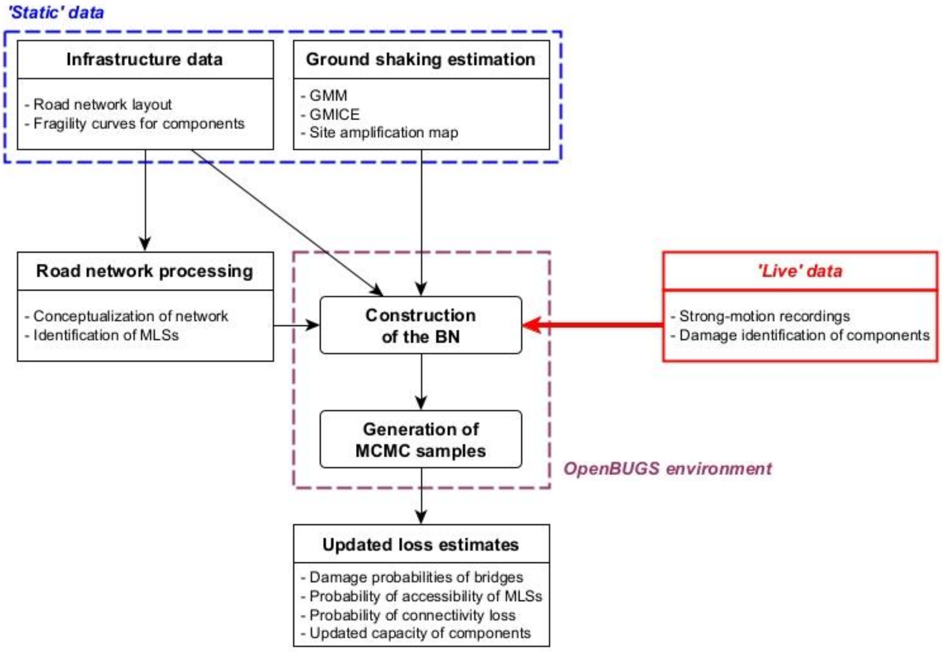

Fig. 1 - Proof-of-concept of the procedure for the rapid earthquake loss assessment of infrastructure systems.

2. Bayesian model

Relying on previous developments regarding the post-earthquake loss assessment of infrastructure systems (Bensi et al., 2013; Bensi et al., 2015; Cavalieri et al., 2017; Gehl et al., 2018), a tool using Bayesian updating is proposed for rapidly estimating losses to road networks. A BN is designed with the OpenBUGS tool (Lunn et al., 2009), which enables the modelling of continuous and discrete variables in the same BN. The OpenBUGS library is freely available, integrated in the R environment (www.r-project.org), and it uses approximate inference via Monte-Carlo Markov-Chain (MCMC) sampling. The developed BN relies on five main types of variables:

• Spatially distributed intensity measure (IM) at the locations of infrastructure components (e.g., road bridges), which represents the distribution of the logarithm of the ground-motion parameter of interest (e.g., peak ground acceleration, PGA). A correlation structure is modelled to represent the contribution of intra- and inter-event error terms of the related ground-motion model (GMM) to the spatial distribution of the IMs at the various sites.

• Seismic capacity (C) of the infrastructure components, which represents the distribution of the logarithm of the seismic response components (e.g., fragility parameters expressed in PGA). A correlation structure may be introduced in order to represent structural similarities between components of the same typology, for instance.

• Damage state (DS) of the components, depending on the IM level at the components' sites and on their seismic capacity C. If only two damage states are considered (i.e., bridge is functional or non-functional), the following convention is adopted: $DS = 1$ if the bridge is intact, $DS = 0$ if non-functional. The assumption of binary damage states is followed for the rest of the study. Therefore, for component i, the damage state DS_i is determined as follows:

$$\begin{cases} DS_i = 0 \text{ if } IM_i > C_i \\ DS_i = 1 \text{ if } IM_i \leq C_i \end{cases} \quad (1)$$

• Accessibility of a minimum link set (MLS) between two locations A and B of the road network. A MLS is defined as a minimum set of components whose joint survival ensures survival of the system (here, the connectivity between A and B). In the case of complex networks containing intersections or alternative routes, multiple MLSs exist between A and B, representing the number of different possible routes to reach the destination. By definition, a MLS represents a sub-system of components in series. The following convention is adopted: $MLS = 1$ if the MLS is accessible and $MLS = 0$ if not. Therefore, for a given MLS k containing p components, the associated variable MLS_k is defined as follows: $MLS_k = DS_1 \text{ x } \ldots \text{ x } DS_p$ (in the case of binary damage states).

• Connectivity between the locations A and B, representing the system performance (S) for this specific objective. In a connectivity analysis, S is then determined by a system of MLSs in parallel (i.e., one accessible MLS is enough to ensure the connectivity between A and B): $S = MLS_1 + \ldots + MLS_q$.

The decomposition of a road network into MLSs is illustrated in Figure 2, where 4 MLSs are identified, each containing a different subset of components. Then, the corresponding BN may be built as shown in Figure 3.

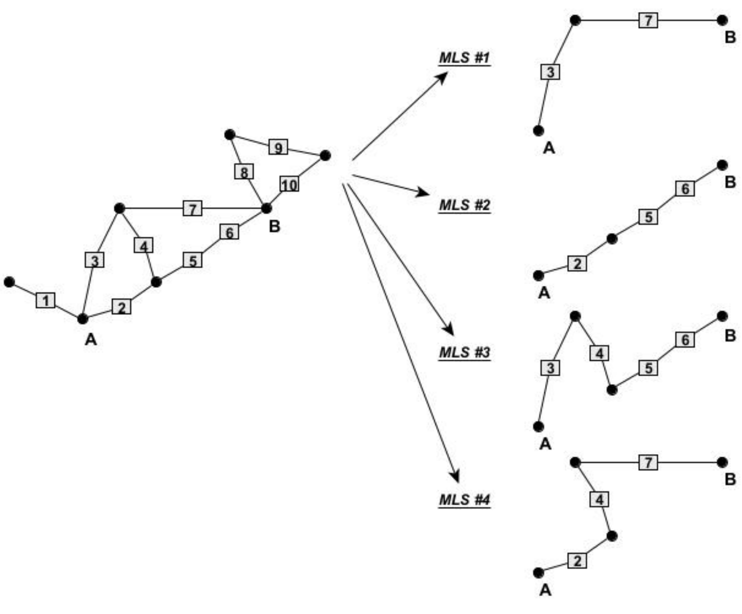

Fig. 2 - Decomposition of the A-B routes into four MLSs, for an illustrative network. Black dots represent intersections in the network, and grey rectangles represent components. The connectivity between A and B constitutes the system performance S.

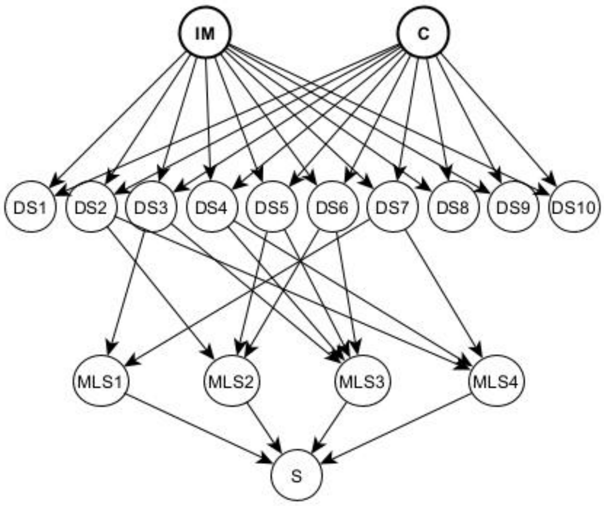

Fig. 3 - BN corresponding to the illustrative example of Figure 2. The node IM is in bold because it represents the vector of spatially correlated IMs at the sites.

Two types of observations may be entered as evidence in the BN:

- Strong-motion recordings by seismic stations, which corresponds to evidence entered at the level of the IM variables;
- Identification of the damage states of some components, e.g. with near-real time structural monitoring (Tubaldi et al., 2021), which corresponds to evidence entered at the level of the DS variables.

With the BN implemented in the OpenBUGS tool, the evidence is then propagated through the related variables. In the inference algorithm, several MCMC chains are initiated: each chain is built with a Gibbs sampling scheme, where variables are successively sampled from the posterior distribution of previous variables. As a result, the BN generates thousands of samples for all variables, which are then assembled to estimate their posterior distributions given the evidence. Examples of these realisations are provided in Table 1 and Table 2, where for a given earthquake event and related field observations, posterior statistics of variables of interest may be extracted from the BN inference.

Table 1. Illustrative example of n MCMC samples for the damage states of the 10 components in Figure 2, assuming $DS_7 = 0$ (failure of component #7) as an evidence.

Sample #	DS_1	DS_2	DS_3	DS_4	DS_5	$DS1_6$	DS_7	DS_8	DS_9	DS_{10}
1	1	1	0	1	1	1	0	0	1	1
2	0	1	0	0	1	1	0	0	0	1
…	0	0	0	1	1	0	0	1	1	0
n	1	1	1	1	1	1	0	1	0	0

Table 2. Illustrative example of n MCMC samples for the accessibility of the 4 MLSs in Figure 2, assuming DS7 = 0 (failure of component #7) as an evidence.

Sample #	MLS_1	MLS_2	MLS_3	MLS_4
1	0	1	0	0
2	0	1	0	0
…	0	0	0	0
n	0	1	1	0

From Table 1 and Table 2, it is possible to extract damage and loss estimates in the form of probabilities, such as $P(DS_i=0)$ the probability of failure of component *i*, or $P(MLS_j=0)$ the probability of MLS *j* being inaccessible.

3. Definition of prior distributions

The prior distributions of the variables that are probabilistically defined (**IM**, **C**) are assumed to follow normal/lognormal distributions, whose parameters are obtained from predictive uncertain models.

In the case of **IM**, the mean of the logarithm of the ground-motion parameter distribution ($\boldsymbol{\mu}_{\mathbf{logIM}}$) is given by a ground-motion model (GMM), based on the earthquake characteristics that are assumed to be known with confidence shortly after the event. The covariance matrix $\sum_{\mathbf{IM}}$ is assembled as follows:

$$\boldsymbol{\Sigma}_{\mathbf{IM}} = \begin{bmatrix} \sigma_\eta^2 + \sigma_{\xi i}^2 & \cdots & \sigma_\eta^2 + \rho_{ij}\sigma_{\xi i}\sigma_{\xi j} \\ \vdots & \ddots & \vdots \\ \cdots & \cdots & \sigma_\eta^2 + \sigma_{\xi j}^2 \end{bmatrix} \tag{2}$$

where σ_η and σ_ξ respectively represent the standard deviations of the inter- and intra-event error terms, which are given by the GMM. The term ρ_{ij} represents the spatial correlation of the intra-event error between sites i and j, and it may be defined by available models in the literature (e.g., Jayaram & Baker, 2009).

The seismic response **C** of components is provided by fragility curves, where the elements of $\boldsymbol{\mu}_{\mathbf{logC}}$ correspond to the median fragility, and the standard deviations of **C** correspond to the fragility dispersion β. The dispersion term β may be further decomposed into β_R and β_M, which respectively represent the uncertainty due to record-to-record variability and the uncertainty due to imperfect knowledge or modelling of the component (Crowley et al., 2019). A third type of uncertainty, related to the definition of the damage state threshold, is neglected here for simplification purposes. Therefore, the covariance matrix $\sum_{\mathbf{C}}$ is expressed as follows:

$$\boldsymbol{\Sigma}_{\mathbf{C}} = \begin{bmatrix} \beta_{Ri}^2 + \beta_{Mi}^2 & \cdots & \rho_{ij}^R\beta_{Ri}\beta_{Rj} + \rho_{ij}^M\beta_{Mi}\beta_{Mj} \\ \vdots & \ddots & \vdots \\ \cdots & \cdots & \beta_{Rj}^2 + \beta_{Mj}^2 \end{bmatrix} \tag{3}$$

The term $\rho^R{}_{ij}$, representing the correlation of the response due to record-to-record variability between components i and j, is very difficult to quantify without the knowledge of the seismic records used in the derivation of the fragility curves. A qualitative rationale may postulate that components i and j – if they are spatially very close to each other – may experience ground motion inputs with similar characteristics in terms of duration, frequency content, etc. and therefore their record-to-record variability should be fully correlated. On the other hand, spatially-distant components are likely to be subjected to different ground-motion (e.g., different spectral shapes), and therefore their record-to-record variability should be uncorrelated. Such considerations are discussed in Silva (2019), who advocates the use of a correlation structure similar to the one that models the spatial correlation of the intra-event error. Although deserving further investigation, this assumption is also used here for the characterization of $\rho^R{}_{ij}$.

The correlation of the component-to-component variability within the same class/typology, represented by $\rho^M{}_{ij}$, also requires more knowledge of how the corresponding fragility curves are derived. Therefore, it is proposed to consider the extreme cases in the application (see Section 4), namely fully correlated or uncorrelated variability, in order to investigate the impact of these assumptions on the posterior distributions. The decomposition of the dispersion into β_R and β_M is not always detailed in available fragility models (i.e., only the global dispersion β is specified). Various assumptions regarding this decomposition are also tested in the application example.

4. Application

4.1. Description of the case-study area

The proposed BN approach for rapid response is applied to a road network composed of 118 bridges (i.e., vulnerable components), which connects 53 municipalities (i.e., built areas) located in a valley around Bagnères-de-Luchon (Pyrenees, France). The case-study area is detailed in Figure 4.

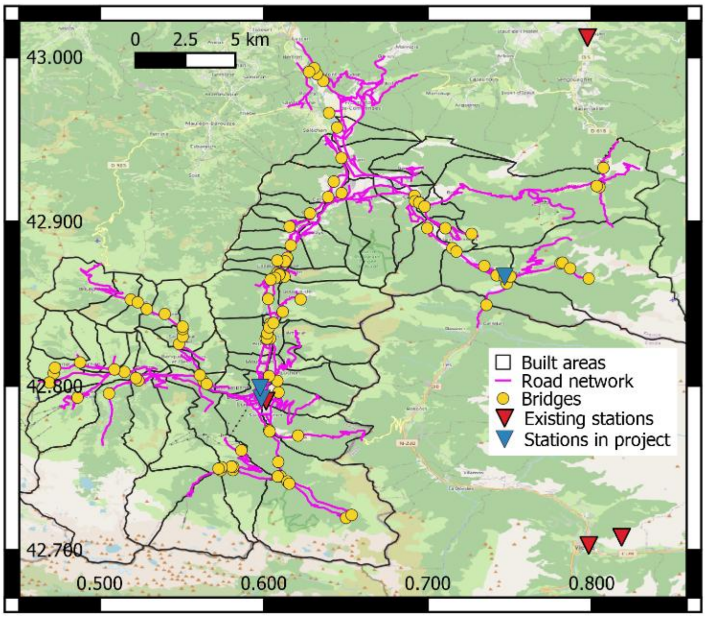

Fig. 4 - Situation map of the Luchon case-study area.

The typologies of the 118 bridges are identified based on photographs and aerial pictures, and their conditional probability of failure is defined by fragility functions, some of which are taken from the SYNER-G database (Crowley et al., 2011). In total, 18 different fragility curves have been assigned (3 models for 83 single-span bridges, 3 for 7 continuous multi-span bridges, and 12 for 28 arch bridges). The fragility curve corresponding to the first limit state is considered as the threshold of the loss of functionality of the bridge (i.e., failure of the component), assuming that even small structural damage might be enough to prevent safe passage.

The studied area is surrounded by several seismic stations (see Figure 4), which are used as sources of observations to constrain estimates of the strong-motion field. All selected fragility curves use PGA as IM; therefore, the regional GMM by Tapia (2006) is applied here for the estimation of the prior distribution of IM. For PGA, the spatial correlation model by Jayaram & Baker (2009) is used with a correlation distance of 8.5 km. Finally, site effects are modelled via soil amplification factors, which were estimated from local investigations and soil measurements (Roullé et al., 2012).

The road network is simplified by considering only paths that need to go through bridges and by building abstract layers of *Super-Nodes* and *Super-Edges* (Gehl et al., 2022), as shown in Figure 5. From this conceptualization step, the MLS decomposition is performed via a recursive algorithm (Cavalieri et al., 2017). The connectivity between the town of Bagnères-de-Luchon (point A) and the Northern part of the network (point B) is investigated here, which leads to 60 MLSs (i.e., 60 different possible routes between A and B).

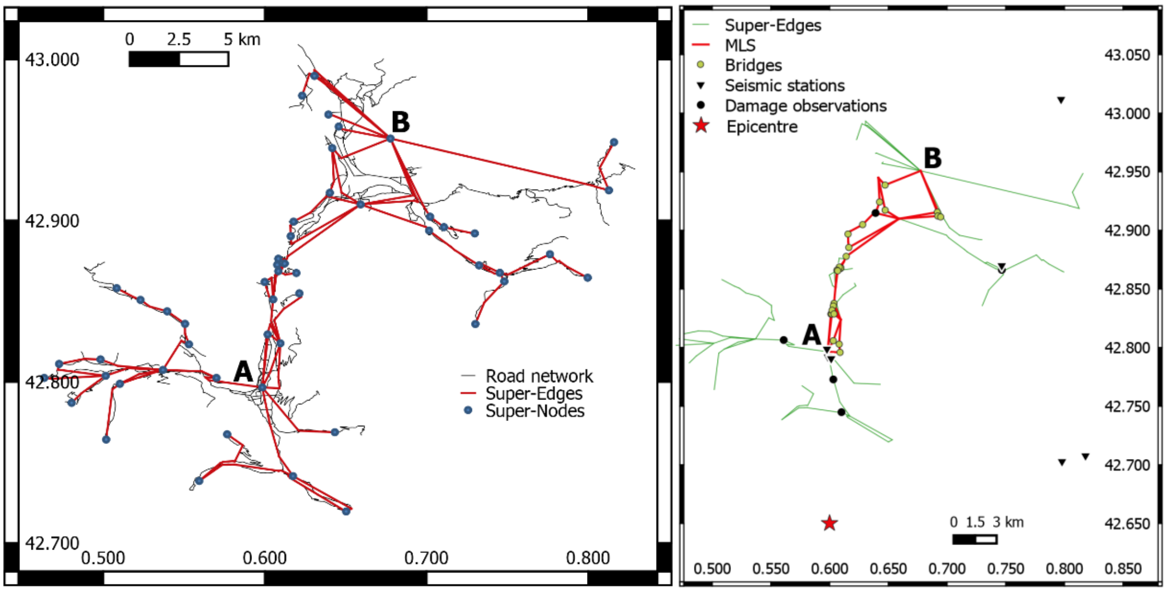

Fig. 5 – Left: abstraction of the network topology for connectivity analysis; Right: MLS decomposition between points A and B of the network.

4.2. Loss updating results

The updating capabilities of the BN are tested with a hypothetical Mw 6.3 earthquake scenario, located south of the road network (0.60° lon, 42.65° lat). Hypothetical observations from 7 seismic stations and damage measures on 5 bridges are set as evidence in the BN (2 survivals and 3 failures). It is assumed that one of the monitored bridges belongs to the identified MLSs, and it has been observed as intact (see Figure 5).

Following the discussion of Section 3 on the assumptions to be made for the covariance models, three different correlation hypotheses are tested for the response **C** of bridges:

- *Corr1*: no correlation is introduced, so that $\sum_{\mathbf{C}}$ is simply a diagonal matrix.
- *Corr2*: only the correlation of the record-to-record variability is introduced, with a correlation model decreasing with inter-bridge distance (i.e., Eq. 3 with $\rho^M{}_{ij} = 0$).
- *Corr3*: in addition to the correlation of the record-to-record variability, a full correlation between bridges of the same type (i.e., using the same fragility model) is assumed, i.e. $\rho^M{}_{ij} = 1$ if bridges i and j are in the same typology.

Global results for the system connectivity are detailed in Table 3, where it is shown that the proposed approach is also able to identify which MLS is the most likely to remain accessible (i.e., "best" MLS).

Table 3. Results of the Bayesian updating, in terms of probability of disconnection between points A and B (i.e., S = 0) and of identification of the "best" MLS, for the various correlation assumptions.

	Prior	Posterior		
		Corr1	*Corr2*	*Corr3*
Pr(Disconnection)	0.095	0.342	0.353	0.435
"Best" MLS	#45	#49	#21	#3

A significant difference is observed between the prior and posterior probabilities of disconnection, due to the assumption that the damage states of 5 bridges were entered as evidence (see Figure 5). The evidence of a bridge's state has an impact on the system at various levels:

• The observation of a bridge failure directly modifies the accessibility of the MLS(s) to which it belongs, and in turn system connectivity.

• If the seismic response **C** is modelled with a constrained correlation model (i.e., *Corr2* or *Corr3*), then the observation of a bridge's state may modify the seismic response of other bridges, in turn modifying their probability of failure and ultimately the accessibility of the MLSs to which they belong.

• Finally, the observation of a bridge's state may also modify the distribution of the IM at the base of the bridge, in turn modifying the ground-shaking field in the vicinity.

The differences between the three correlation models are noticeable: the extreme configurations *Corr1* and *Corr3* should be used as upper and lower bounds of the model outcome, pending an in-depth investigation of appropriate correlation models for the seismic response. Furthermore, each assumption leads to the identification of a different MLS as the least affected route, which could have a large impact on emergency operations. An example of the changes in the rapid estimate of the post-earthquake condition of the network is provided in Figure 6, both in terms of failure probability of bridges and identifying the most accessible MLS.

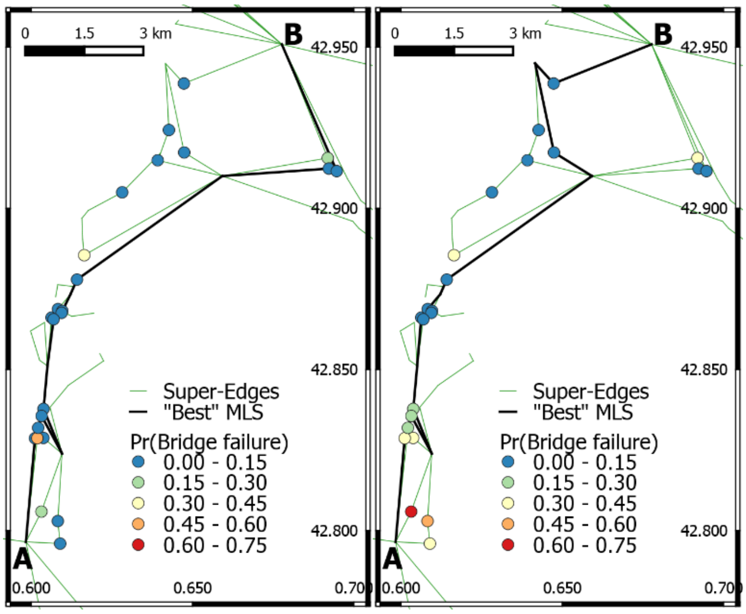

Fig. 6 - Left: prior distribution using only the characteristics of the earthquake event; Right: posterior distribution using field observations (with *Corr3* model).

5. Conclusions

This study has investigated the implementation of a Bayesian Network-based framework for improving situational awareness during the rapid response phase following an earthquake event. It has been demonstrated that a BN built in OpenBUGS environment is able to provide updated losses for a real-world road network and built areas based on available observations. The BN is solved with a MCMC sampling scheme, which delivers approximate posterior distributions: this approximate solution, as opposed to exact inference algorithms, is a necessary trade-off in order to treat systems of hundreds of components exposed to spatially distributed hazards. Moreover, the sampling inference scheme used in OpenBUGS can combine continuous (e.g., intensity measures, seismic capacities) and discrete variables (e.g., damage states), which has the benefit of introducing exact distributions instead of discretizing continuous variables. Regarding road networks, when connectivity loss is used as a simple system indicator, the decomposition of the system into MLSs is also essential in reducing the complexity of the BN. As a result, in the studied example, posterior distributions are generated within 20 or 30 minutes. Moreover, the decomposition into MLSs has the benefit of identifying specific routes associated with probabilities of accessibility: this information has the potential to be used by emergency managers to set up dedicated evacuation routes or safe itineraries to hospitals. Each MLS can also be associated with a travel distance or travel duration, in order to develop more elaborate performance indicators than connectivity loss. Finally, the results of such a BN application can constitute the starting point of rapid repair strategies for bridges, in order to improve the seismic resilience of transportation systems (Sun et al., 2021).

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